Nondestructive Evaluation for Active Safety & Smart Health Care for Prognosis

KAERI – Intelligent Computing Laboratory

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Contents

Who is Hogeon?

- ## 연구분야

IoT 센서 딥러닝	Ultra-wide Band (**UWB**) Radar, Electroencephalography (**EEG**), **Sound**, **Ultrasound**
초음파 영상화	Total Focusing Method (**TFM**), Synthetic Aperture Focusing Technique (**SAFT**)
레이저 초음파	Surface Acoustic Waves (**SAW**), Ultrasonic Propagation Imaging (**UPI**)
비선형 초음파	Acoustic Nonlinearity, Contact Acoustic Nonlinearity (**CAN**)
NDT 시스템 개발	**Python**, **MATLAB**, **LabVIEW**, C#, Android, **Arduino**, **PyTorch**, TensorFlow

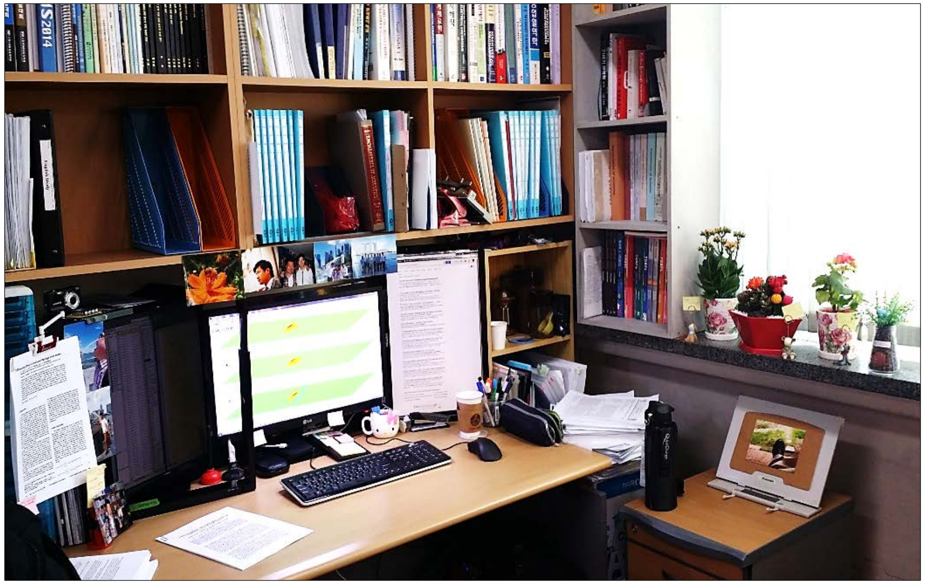
- ## 학력 및 경력

한국원자력연구원 - 지능형컴퓨팅연구실 (유용균 실장님)	선임연구원	2019 - 현재
광주과학기술원 - 인공지능 연구실 (이규빈 교수님)	박사후연구원	2018 - 2019
한양대학교 - 공학박사	융합기계공학	2013 - 2018
한양대학교 - 지능계측 및 비파괴평가 연구실 (장경영 교수님)	학생연구원	2012 - 2018
한양대학교 - 공학사	기계공학	2006 - 2013

- ## 수상 및 장학 내역

한국스마트미디어학회 - SMA 2019 우수논문상	한국스마트미디어학회	2019
한국로봇종합학술대회 - KROC 2019 신진연구자상	한국로봇학회	2019
글로벌박사양성사업 선정자	한국연구재단	2013 - 2018
성옥문화재단 장학생	성옥문화재단	2011 - 2013
기계공학종합설계 동문회장상	한양대학교	2012

한양대학교 - 지능계측 및 비파괴평가 연구실 (2012~2018)



한양대학교 - 지능계측 및 비파괴평가 연구실 (2012~2018)

- **비파괴평가 관련 연구개발 수행 이력** @ 한양대학교 지능계측 및 비파괴평가 연구실

2017.06-2017.07	**국제 공동연구-레이저 초음파 :: 한양대- Le Mans University**	LAUM@프랑스
2017.04-2018.02	**초음파를 활용한 알루미늄 잔류응력 비파괴평가 기술 개발**	삼성전자 GTC
2016.03-2016.11	**표층부 결함 진단을 위한 레이저 초음파 평가 시스템 개발**	삼성전자 GTC
2014.02-2014.06	**비파괴 검사를 이용한 Defect 및 물성측정에 관한 기술 자문**	삼성전자 GTC
2013.07-2018.02	**산업구조재의 잠닉손상 진단을 위한 선형/비선형 하이브리드 초음파 기술 개발**	NRF
2013.03-2018.02	**레이저 여기 표면파의 비선형 주파수 특성을 활용한 재료 물성변화의 평가**	NRF
2012.11-2012.12	**고출력 레이저에 의한 손상 분석 연구**	국방과학연구소
2012.07-2013.06	**극미세 재료손상진단을 위한 비선형초음파기술 개발**	NRF
2012.04-2012.10	**원전설비 손상 조기진단 위한 레이저기반 비선형 표면파 기술개발**	에기평

광주과학기술원 - 인공지능 연구실 (2018-2019)

광주과학기술원 - 인공지능 연구실 (2018-2019)

- **인공지능 관련 연구개발 수행 및 참여 이력** @ 광주과학기술원, 인공지능 연구실

2019.04-2019.11	**조립 설명서로부터 비정형 멀티 모달 정보를 이해하여 실·가상환경에서 가구조립을 위한 작업 계획을 생성·검증하는 AI 기술 개발**	과기정통부
2019.04-2019.11	**AI기반 금형부품 형상인식 기술개발**	삼성전자
2019.04-2019.11	**소리-햅틱 변환을 위한 딥러닝 기반 음성 검출 연구**	동운아나텍
2019.04-2019.11	**설치가 용이한 지능형 다관절 식사보조 로봇 개발**	산업통상자원부
2019.02-2019.11	**로봇 시운동을 위한 가상환경에서 실제환경으로의 심층강화학습**	광주과학기술원
2019.01-2019.11	**GIST 맞춤형 인공지능 연구 방향 수립**	광주과학기술원
2019.01-2019.02	**노약자 지원 기술 개발 (영상 데이터 딥러닝)**	광주과학기술원
2018.03-2019.11	**인공지능 기반 수면 분석 및 수면 무호흡 증후군 진단 알고리즘 연구**	광주과학기술원
2018.03-2019.11	**AR글래스 기반 도슨트 운용을 위한 지능형 UI/UX 기술 개발**	문화체육관광부

한국원자력연구원 – 지능형컴퓨팅연구실 (2019-뼈를 묻을 때까지)

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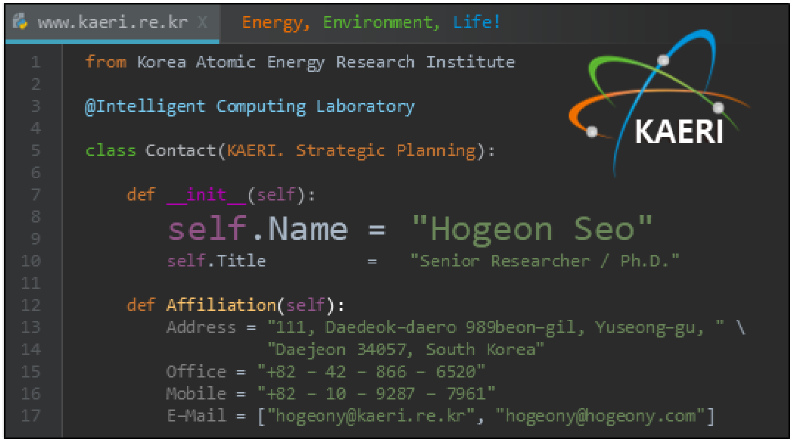

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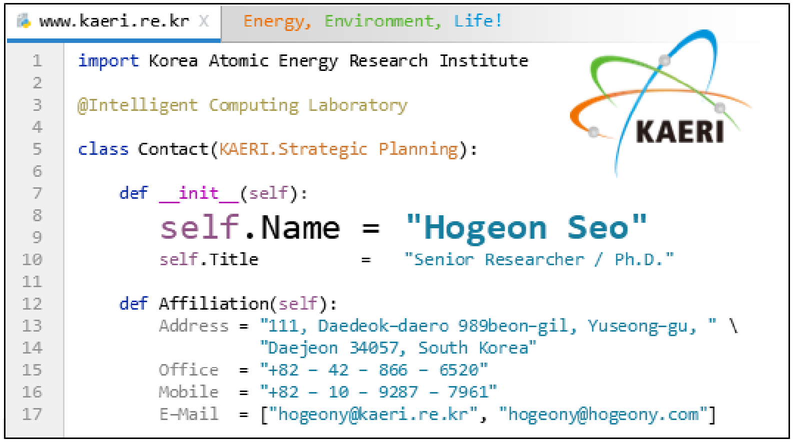
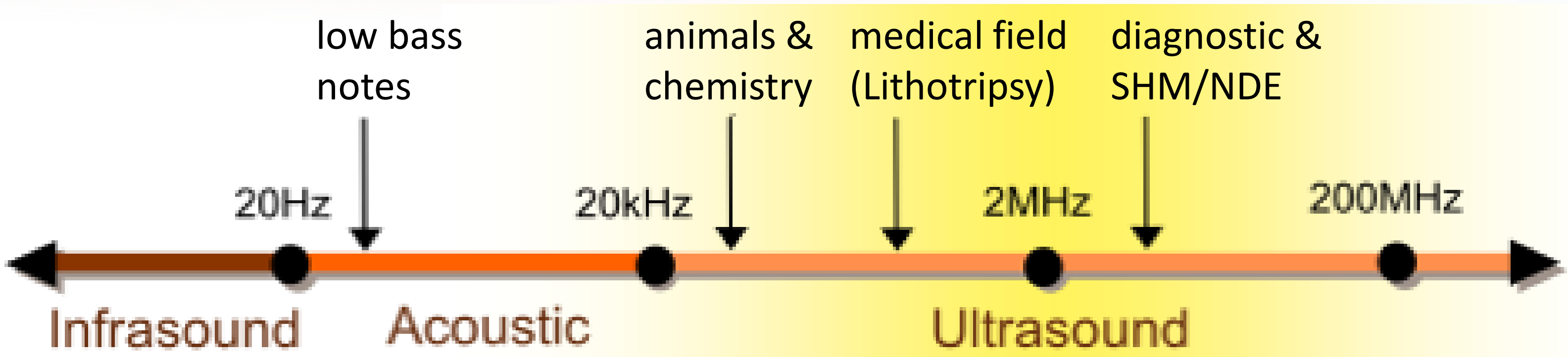


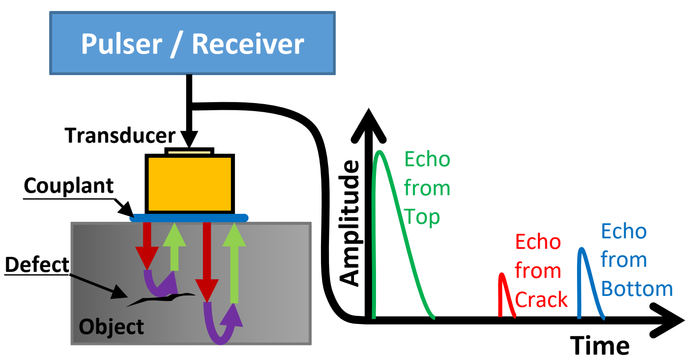
Contents

What is Ultrasounds & Nondestructive Evaluation / Test

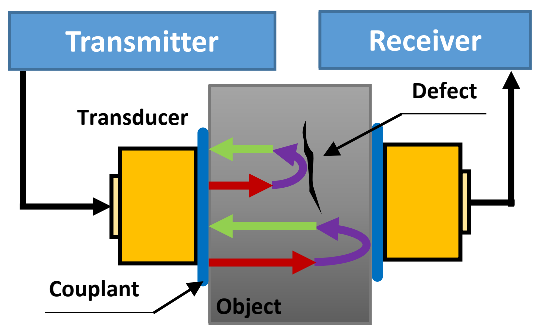
◉ Sound



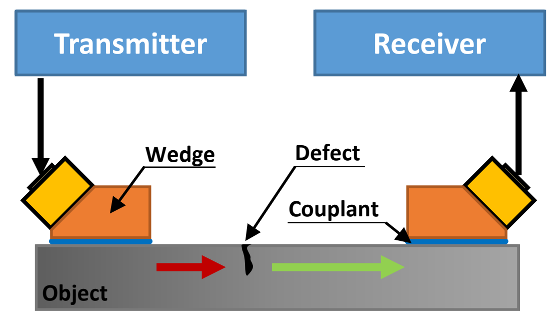
◉ Pulse-echo Mode



◉ Through-transmission Mode



◉ Pitch-catch Mode



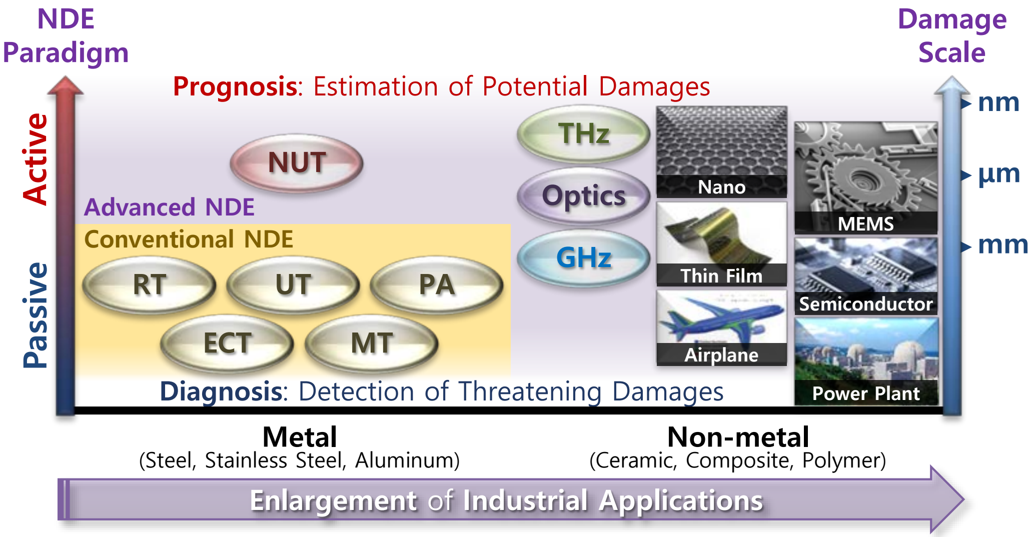
- Ultrasounds can be generated by Contact & Non-contact Method
  : **Piezo-electric Transducer, Impact, Laser Beam**

Nondestructive Evaluation for Active Safety

Sophisticated Inspection of Aging Structures is Essential :: Research Backgrounds

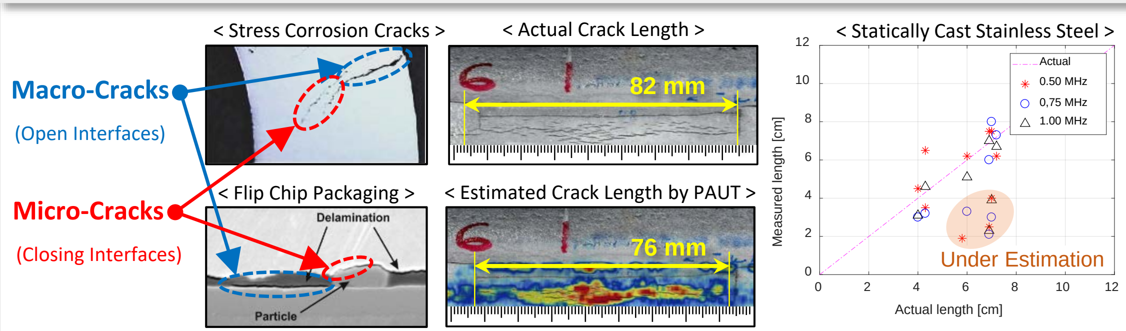
- **Industrial Structures prepare for Old Age**
  - Aircraft: 10.3 Years, 10.6% (> 20 Years)
  - Nuclear Plant: 23.2 Years (61.7% of Lifespan)
- **Paradigm Shift in Nondestructive Evaluation**
  : Passive Safety → Active Safety

➤ **Nonlinear Ultrasonic Testing is Sensitive to Micro Cracks & Material Degradations**

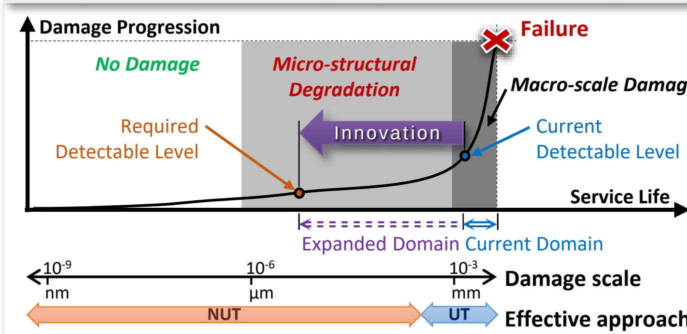


Early-Stage Damage Detection via Nonlinear Ultrasonics :: Research Objectives

Flaws (Stress Corrosion Crack, Unbonded Interface)



Degradations (Aging, Creep, Fatigue)



Thesis for Ph.D., Synthetic Aperture Imaging of Acoustic Linearity and Nonlinearity (2018)   http://repository.hanyang.ac.kr/handle/20.500.11754/68340

Nonlinear Ultrasonics :: Acoustic Nonlinearity (AN)

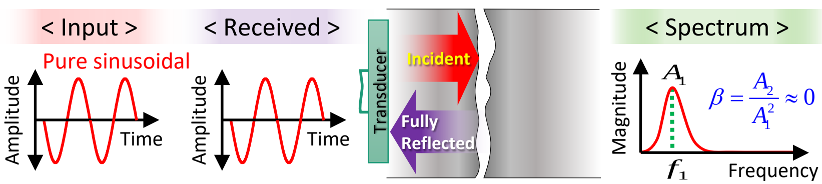
Contact Acoustic Nonlinearity

✓ Clapping Phenomenon occurs at Closing Interfaces, which causes Harmonic Frequency Components

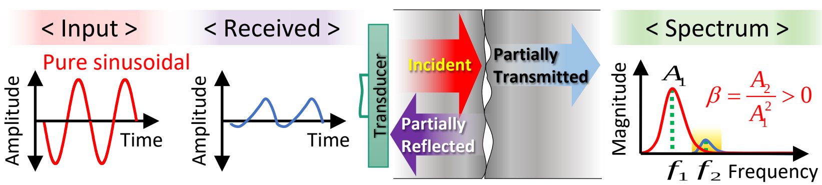
✓ **Detection of Crack Tip & Unbonded Part**

→ **Accurate Crack Sizing** to avoid Under-Estimation

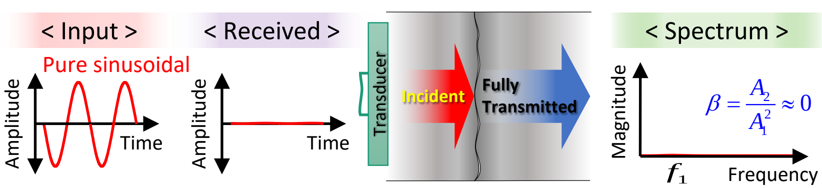
- **Open Interface** :: Macro-Crack



- **Closing Interface** :: Micro-Crack (Crack Tip) → **CAN**

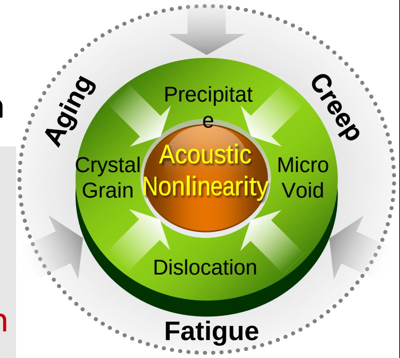


- **Closed Interface** :: Intact Part



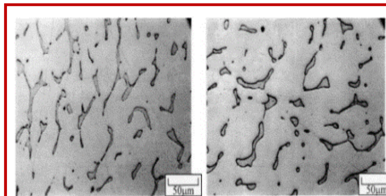
Material Acoustic Nonlinearity

✓ Micro-Structural Changes causes Harmonic Generation

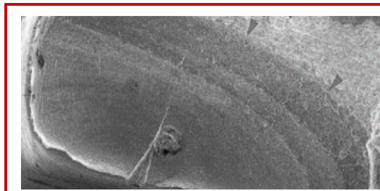


✓ **Evaluation of Material Degradations**

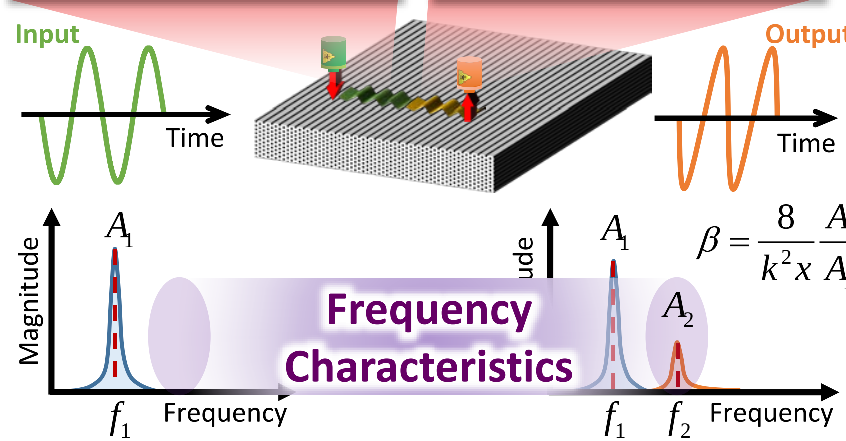
: Thermal-aging, Deformation



Thermal Aging, Creep



Fatigue, Deformation

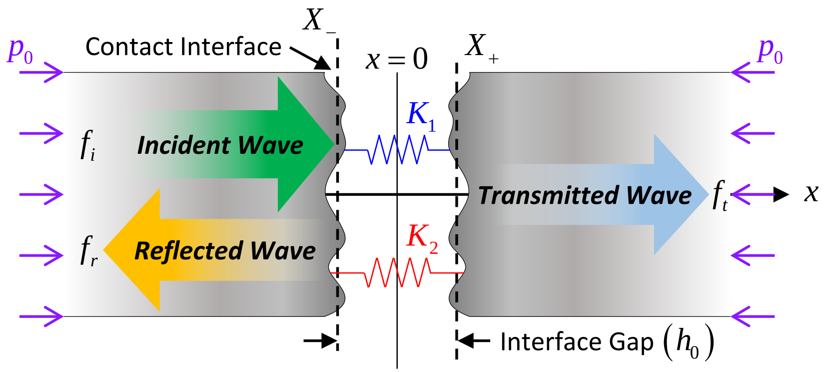


Metals, 10(1), 38 (2020), IF: 2.259 @ 2018

https://doi.org/10.3390/met10010038

Contact Acoustic Nonlinearity at Closing Interfaces

Modeling & FEM Simulation



- **Governing Equation**

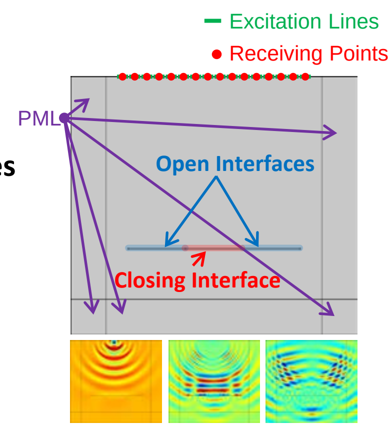
$$\rho\frac{\partial^2\mathbf{u}}{\partial t^2}=\nabla\cdot\sigma+\mathbf{F}_V$$

- **Boundary Condition for Interfaces**

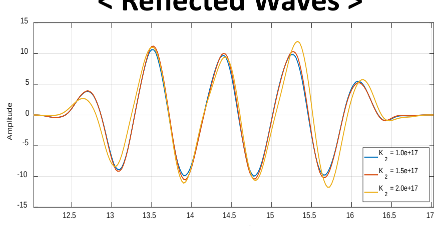
$$F(t)=K_1\left[h(t)-h_0\right]+K_2\left[h(t)-h_0\right]^2$$

- **Contact Acoustic Nonlinearity**

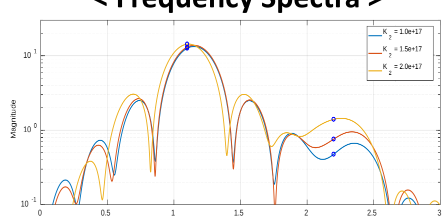
$$\beta=\frac{A_2}{A_1^2}=\frac{K_2}{\sqrt{(\rho c\omega)^2+(K_1)^2}}$$



< Reflected Waves >



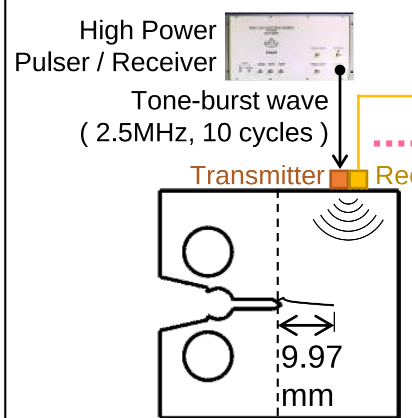
< Frequency Spectra >



Experimental Verification

✓ **Second Harmonic Frequency Component (A_2) was observed at Closing Interfaces of Crack Tip**

✓ **Crack Length Sizing was More Accurate when considering Nonlinear Frequency Components**



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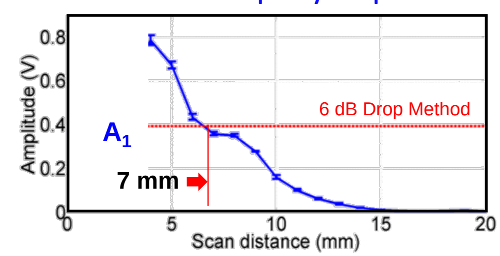
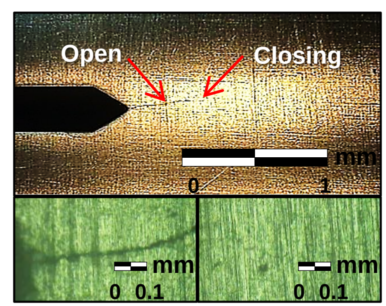
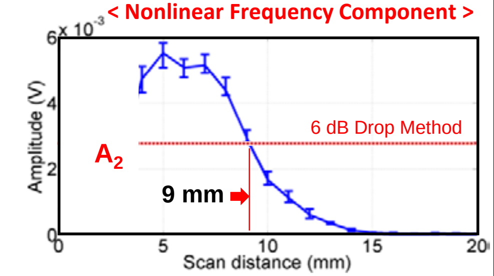




< Nonlinear Frequency Component >



International Journal of Precision Engineering and Manufacturing, 15.11, 2461-2464 (2014), IF: 1.779 @ 2018 http://dx.doi.org/10.1007/s12541-014-0614-4

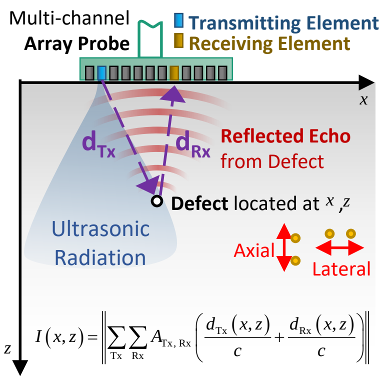
Ultrasonic Imaging for Micro-Crack Detection

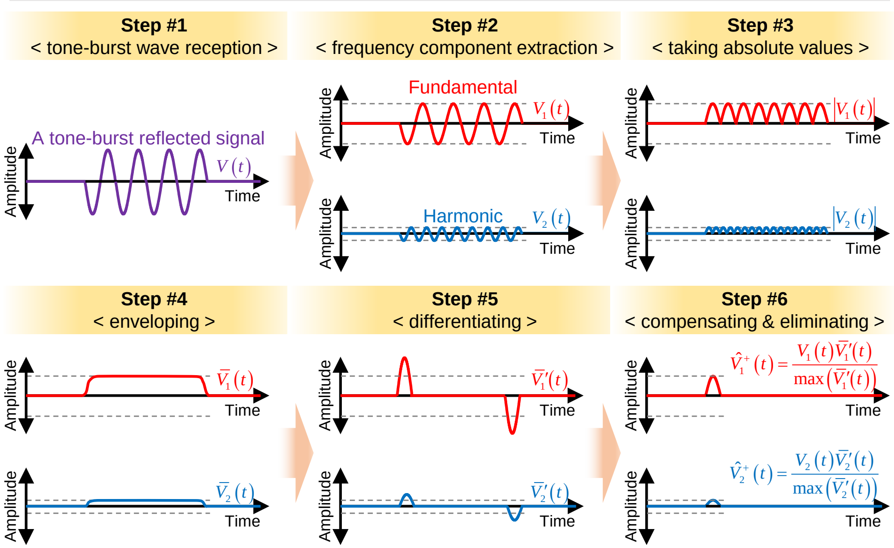
Synthetic Aperture Imaging of AN

- Synthetic Aperture Imaging is based on Pulse Wave
- For AN Measurement, Tone-Burst Wave is Suitable due to Narrow Bandwidth

✓ Convergence of SAI and AN was achieved by Waveform Conversion Algorithm

: **Synthetic Aperture Imaging of Acoustic Nonlinearity**

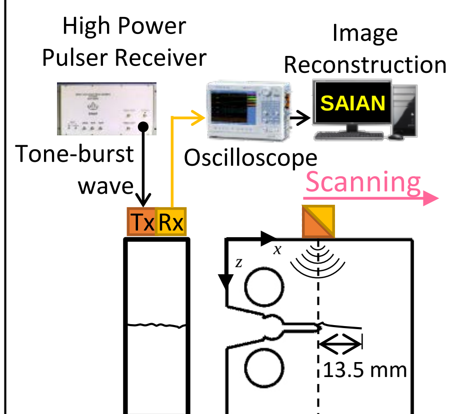


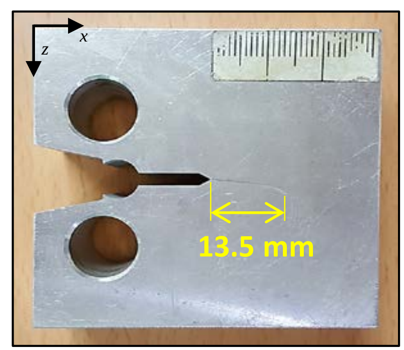


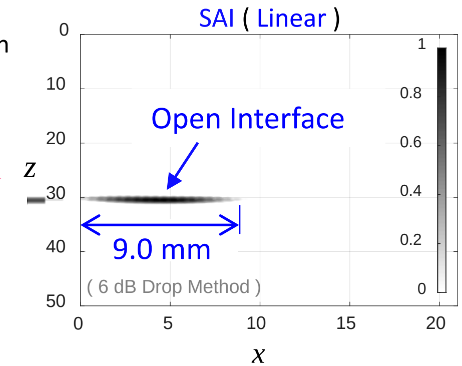
SAIAN for Crack Tip

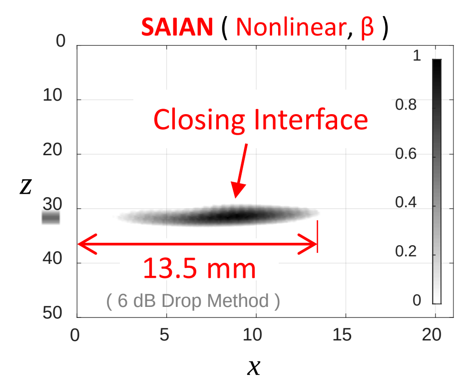
✓ SAIAN visualized Contact Acoustic Nonlinearity (β) at Closing Interfaces of Crack Tip

✓ Imaging & Sizing of Crack was More Accurate when using Combination of Linear & Nonlinear SAI









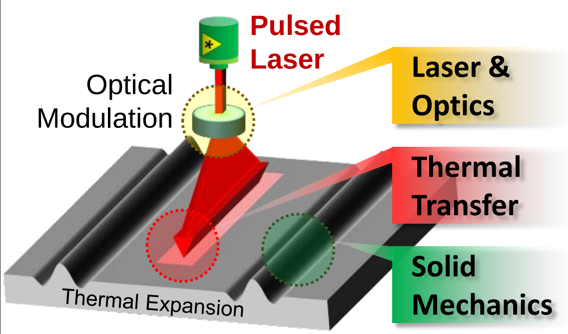
Mechanical Systems and Signal Processing, 125, 257-274 (2019), IF: 5.005 @ 2018

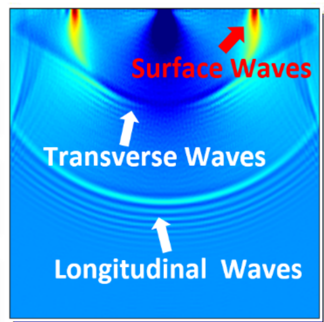
https://doi.org/10.1016/j.ymssp.2018.08.025

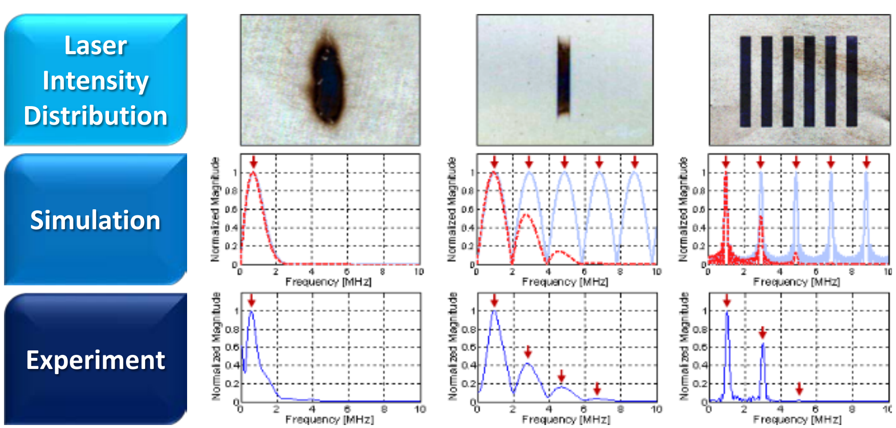
Acoustic Nonlinearity of Laser-generated SAW

Laser Ultrasonics

- **Laser Energy heats up and cools down,** which makes Longitudinal, Transverse, Surface Waves
- **Laser-generated Surface Waves are Effective to inspect the Parts with Limited Access**

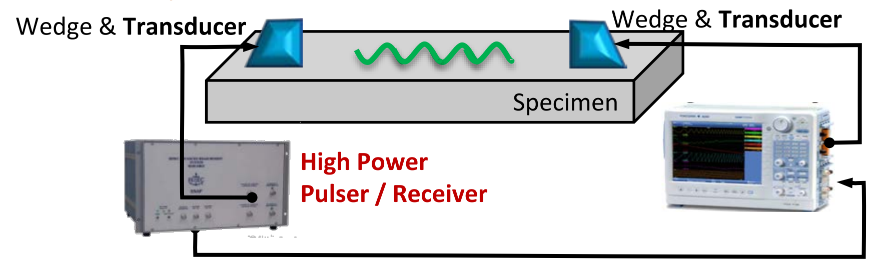




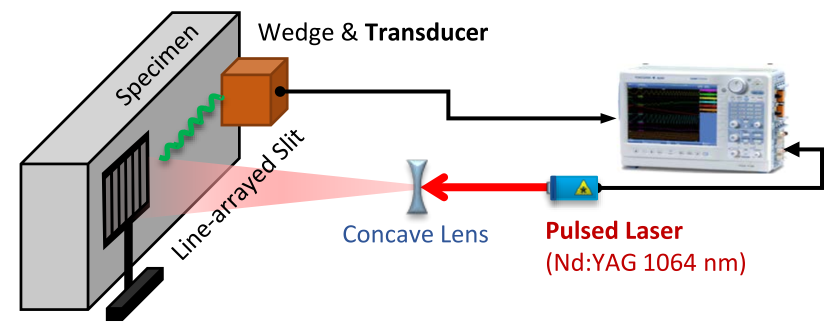


Surface Acoustic Waves for NDE

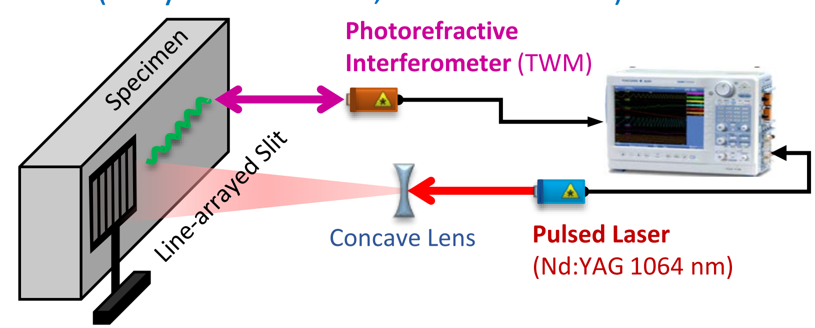
- **SAW** (Fully Contact, PZT – PZT)



- **LSAW** (Semi Non-contact, LASER – PZT)



- **LSAW** (Fully Non-contact, LASER – LASER)

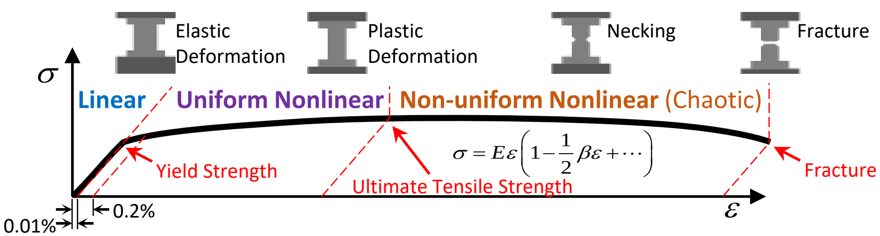


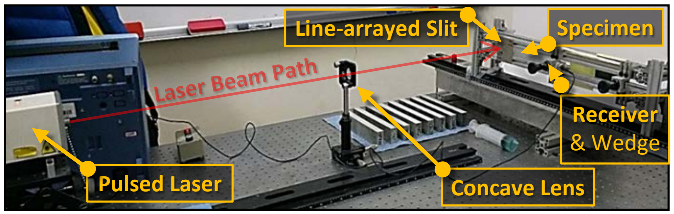
Journal of the Korean Society for Nondestructive Testing, 36(2), 138-148 (2016)
https://doi.org/10.7779/JKSNT.2016.36.2.138

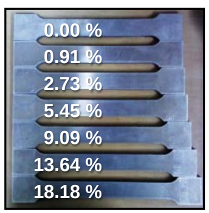
Laser Ultrasonics for Structural Health Monitoring

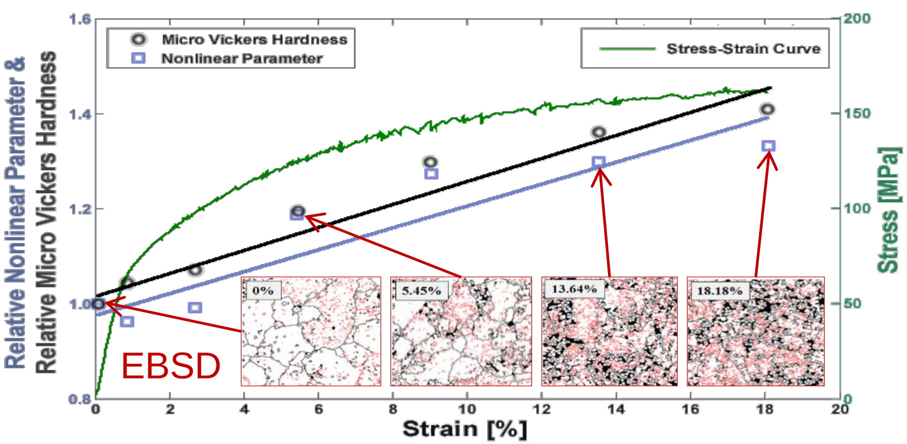
Plastic Deformation Evaluation

✓ **Acoustic Nonlinearity increased according to Plastic Deformation** (Strain Rate, Vickers Hardness)



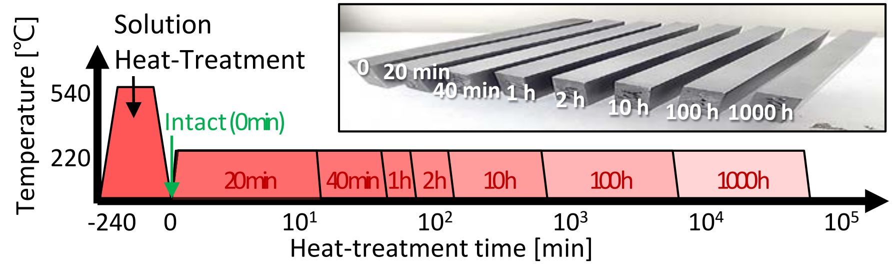


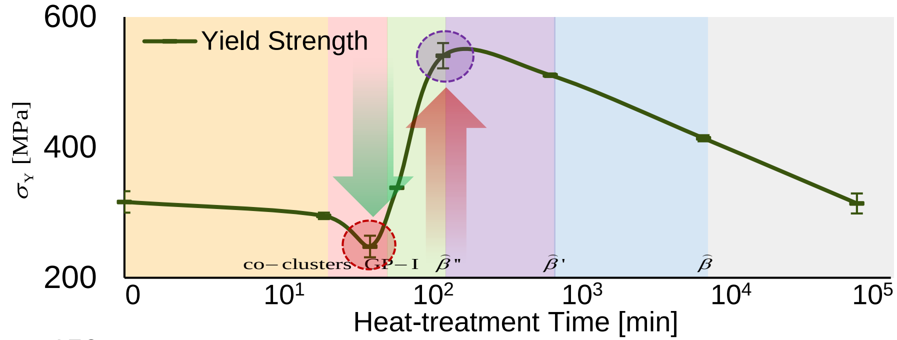


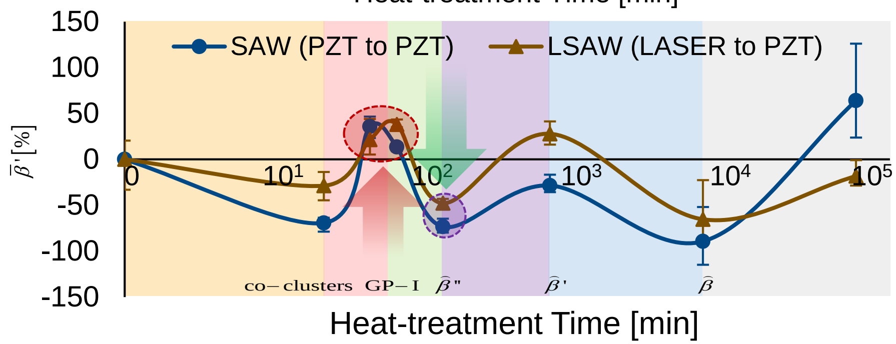


Thermal-aging Evaluation

✓ **Acoustic Nonlinearity showed Characteristic Change according to the Variation of Yield Strength**



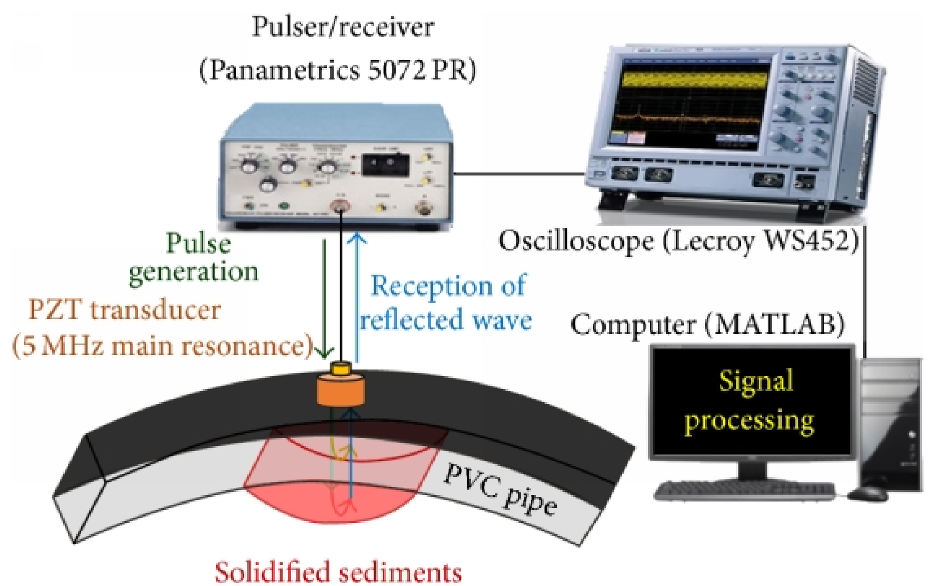


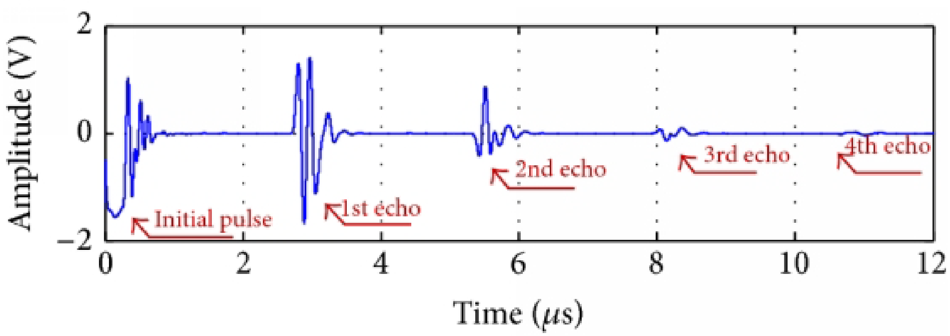


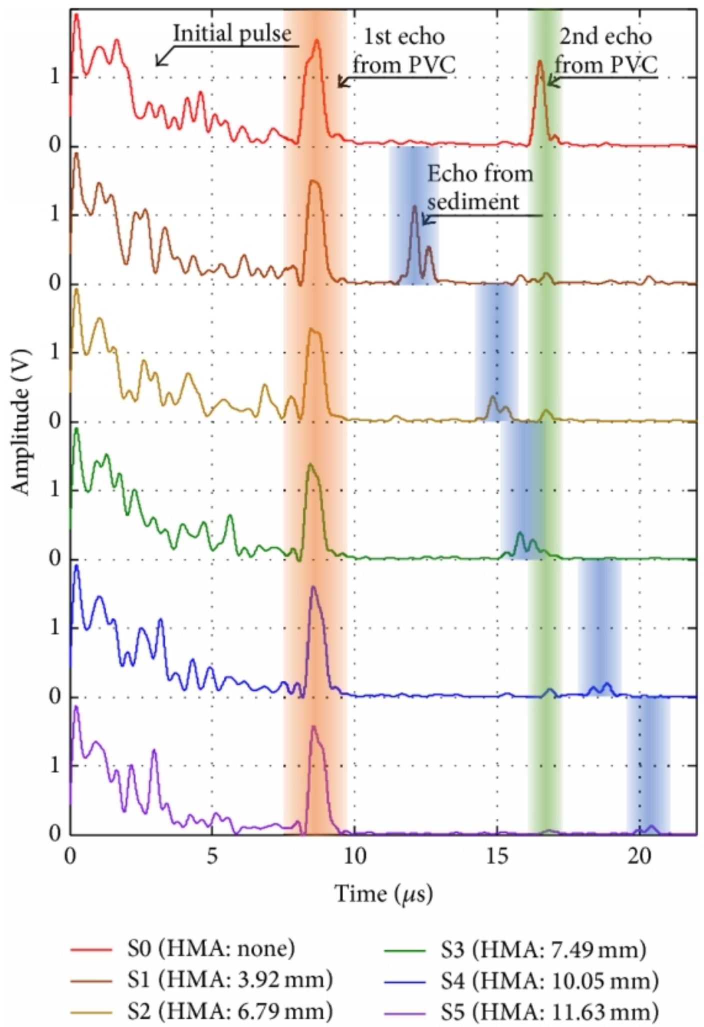
Research in Nondestructive Evaluation, 28.1, 3-17 (2017), IF: 1.517 @ 2018

http://dx.doi.org/10.1080/09349847.2016.1261213

- 실시간 PVC 배관 내부 적층물 두께 검사 (접촉식 초음파, 선형 초음파 특성)



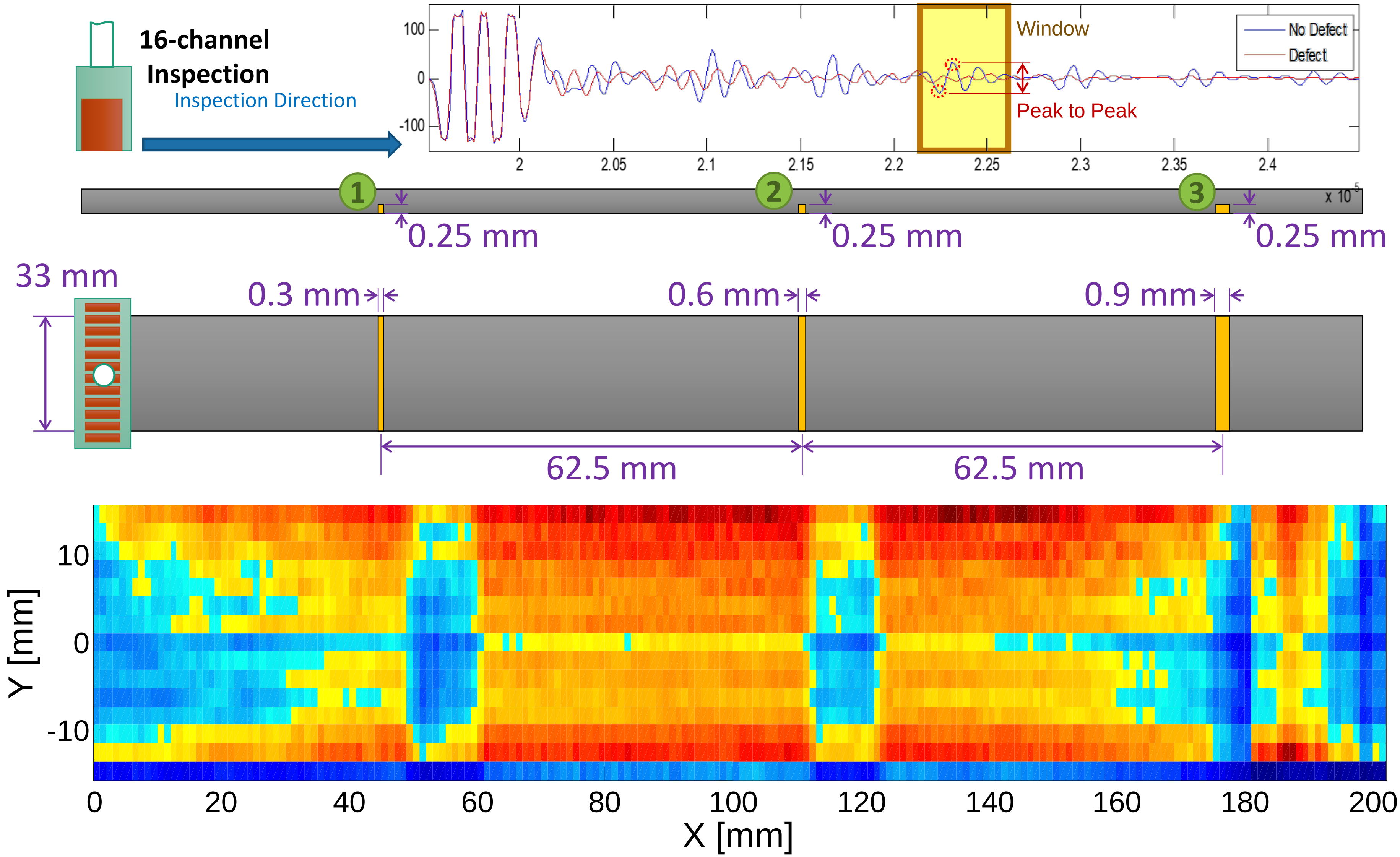




The Scientific World Journal, 731621 (2014), IF: 2.43 @ 2013
http://dx.doi.org/10.1155/2014/731621

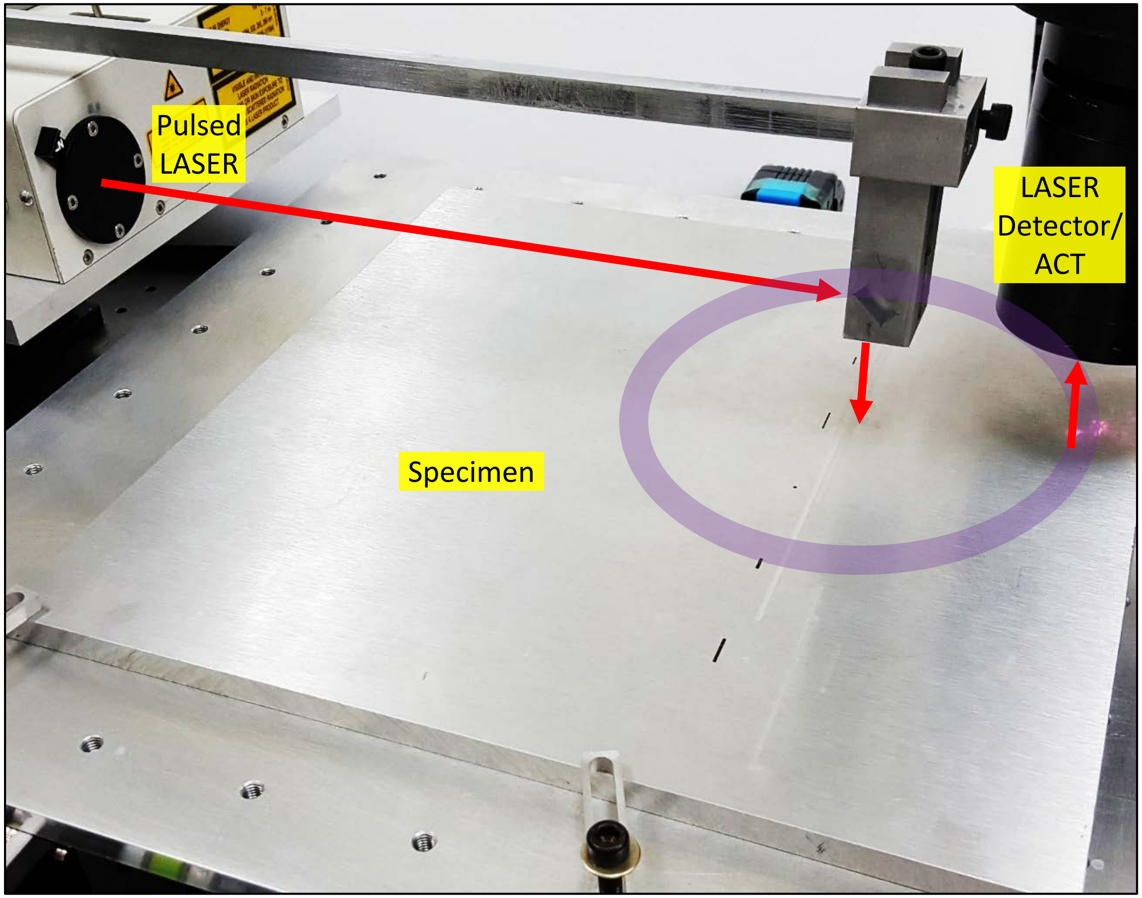
수중 선형 초음파 신호 영상화를 통한 비파괴검사 적용 사례

- 얇은 판재의 Notch 결함 Pulse-echo Mode 초음파 스캔 영상화 (cf. 방사성폐기물 드럼통)



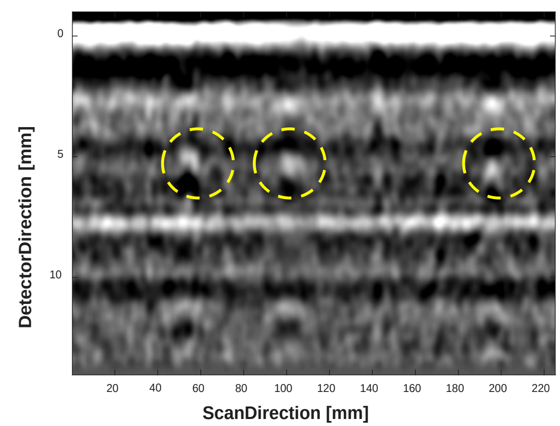
펄스 레이저에 의한 초음파 발생 및 전파를 통한 결함 영상화

- 레이저 표면파를 활용한 표면 및 표면 직하 결함 영상화



1 mm 깊이 표면 결함 시편 사진

레이저 초음파 평가 시스템 진단 결과



International Journal of Precision Engineering and Manufacturing, 16.13, 2641-2645 (2015), IF: 1.779 @ 2018 https://doi.org/10.1016/j.ymssp.2018.08.025

Research in Nondestructive Evaluation, 26.1, 13-22 (2015), IF: 1.517 @ 2018 http://dx.doi.org/10.1080/09349847.2014.934496

Applied Sciences, 9 (6), 1191 (2019), IF: 2.217 @ 2018 https://doi.org/10.3390/app9061191

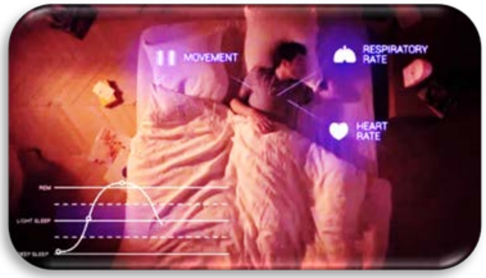
Contents

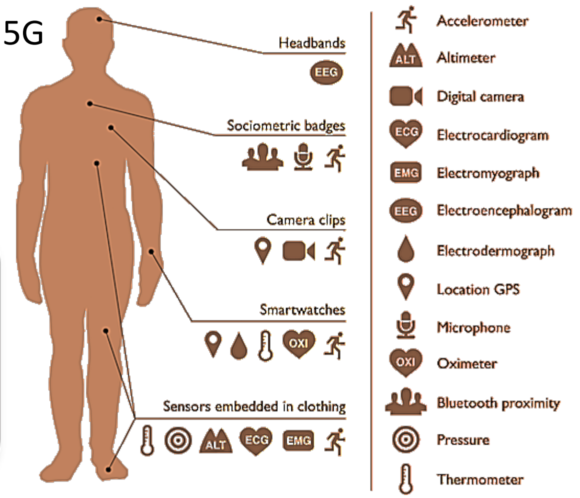
Health Care for Prognosis

Always-On Remote Health Care is Coming :: Research Backgrounds

- Health Care 4.0 is based on Cloud Computing (AI), Big Data, Internet of Things, 5G
- **Enormous Amount of Bio Data can be used for Prognosis of Diseases**
- **Noncontact Sensing is Practical and Effective for Always-on Monitoring**

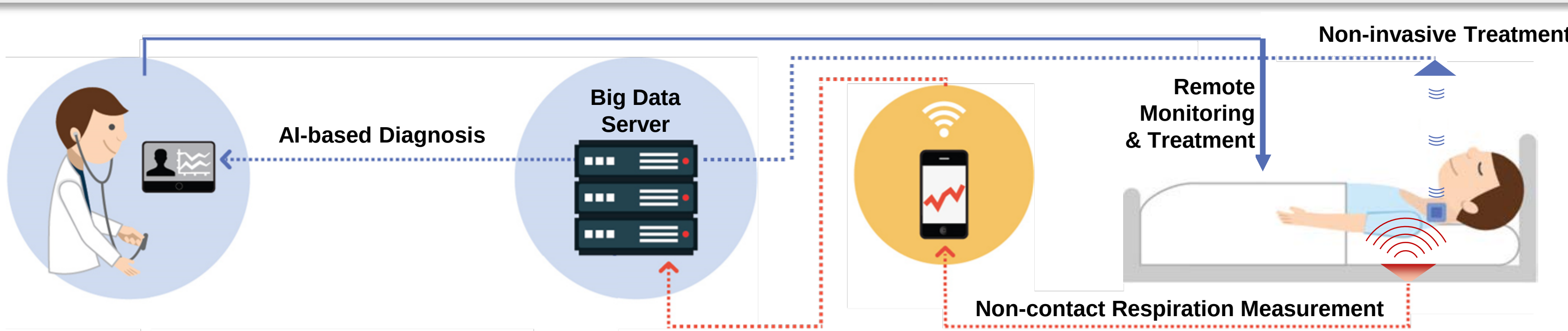
> **Prognosis based on Noncontact Monitoring has Great Potential Value in Health Care 4.0**
>
> About 30% of Human Life are Sleep
>
> → **Sleep-related Prognosis is Essential**





Early-Stage Disease Diagnosis via Noncontact Monitoring :: Research Objectives

Smart Health Care (Noncontact Condition Monitoring, Adaptive Noninvasive Treatment)



Noncontact IoT Technology: WiFi, Bluetooth, UWB, RFID

Real-time locating systems (RTLS) are used to automatically identify and track the location of objects or people in real time, usually within a building.

Technology	Accuracy	Range	Suitable for	Tracking	Transmitter power supply	Battery lifetime
Wi-Fi	< 15 m	< 150 m	area detection		or	medium
BLE	< 8 m	< 75 m	area detection			high
UWB	< 30 cm	< 150 m	area detection		or	low to medium
RFID	< 10 cm	< 1 m	spot detection		— (passive RFID tag)	— (passive RFID tag)

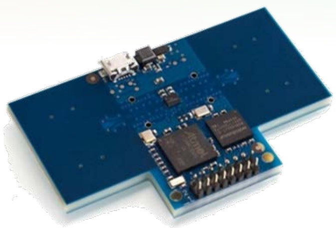
Use Recommendations

- **Wi-Fi**: tracking solutions (e.g. for event locations)
- **Bluetooth** (BLE): indoor tracking solutions without near perfect precision needs
- **UWB**: tracking solutions in industrial environments with high precision needs
- **RFID**: tracking solutions with large number of tags (e.g. in logistics, inventory management)

Standard Strength of Electromagnetic Waves for Humans

- **Ultra-wide Band (UWB) Radar = X4M200 (Novelda, Norway)**

  - Frequency: about 7.29 GHz,   Size: 68 mm x 42 mm x 7 mm
  - Detecting Range: < 9.87 m,   Distance Resolution: 1 ∽ 2 cm
  - Transmitter Bandwidth (-10 dB):   1.4 GHz
  - Receiver Bandwidth: 6.5 or 10 GHz
  - Energy per Pulse: 0.45 ~ 2.6 pJ
  - Maximum Pulse Repetition Frequency: 40.5 MHz




XETHRU

기술	투과 전력 [W]	전기장 강도 @ 40 cm [V/m]	보호기준 대비
5.0 GHz 와이파이	1.000000	13.690	22.4%
3G 스마트폰	0.500000	9.680	15.9%
2.4GHz 와이파이	0.100000	4.330	7.1%
노트북 무선랜	0.032000	2.450	4.0%
블루투스	0.002500	0.680	1.1%
XeThru UWB	0.000084	0.126	0.2%

B679-3EEC-473D-4D64

방송통신기자재등의 적합인증서

Certificate of Broadcasting and Communication Equipments

상호 또는 성명 Trade Name or Applicant	NOVELDA AS
기자재명칭(명칭) Equipment Name	UWB 및 용도미지정기기(UWB 기술을 사용하는 기기)
기본모델명 Basic Model Number	X4M07
파생모델명 Series Model Number	
인증번호 Certification No.	R-CRM-N1A-X4M07
제조자/제조국가 Manufacturer/ Country of Origin	NOVELDA AS / 노르웨이
인증연월일 Date of Certification	2018-01-17
기타 Others	

위 기자재는 「전파법」 제58조의2 제2항에 따라 인증되었음을 증명합니다.

It is verified that foregoing equipment has been certificated under the Clause 2, Article 58-2 of Radio Waves Act.

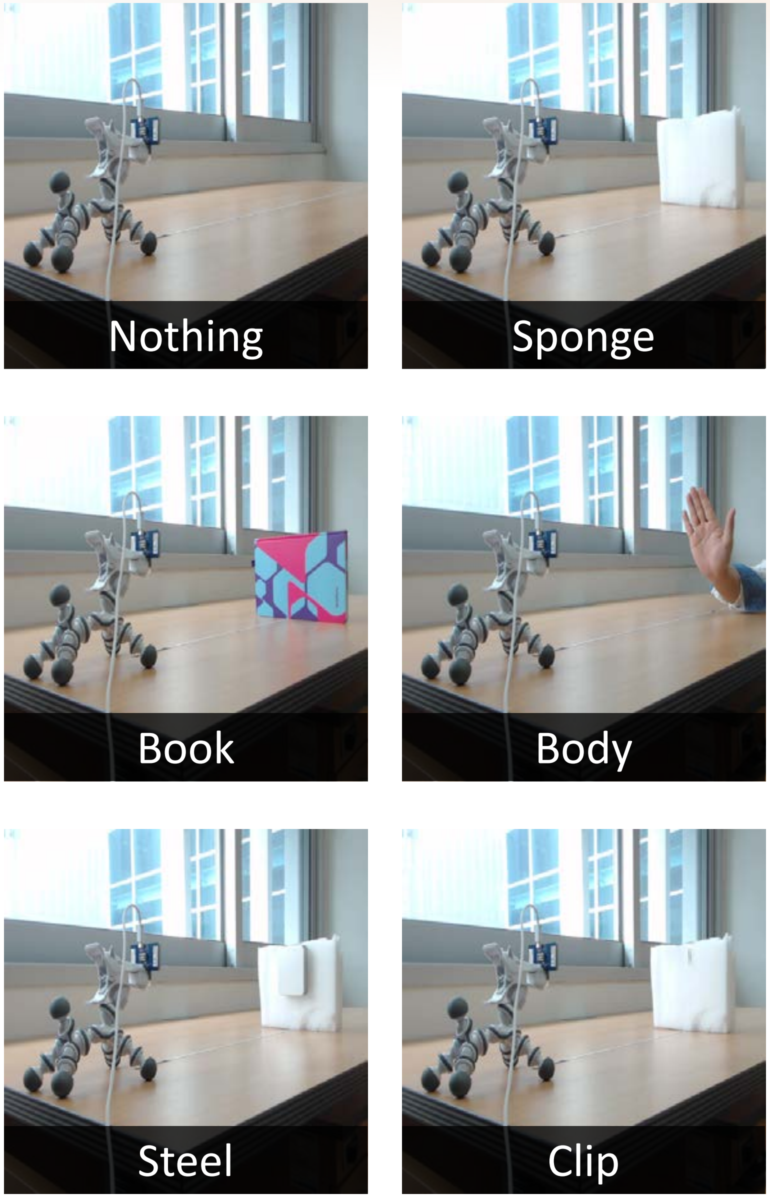
2018년(Year) 01월(Month) 17일(Day)

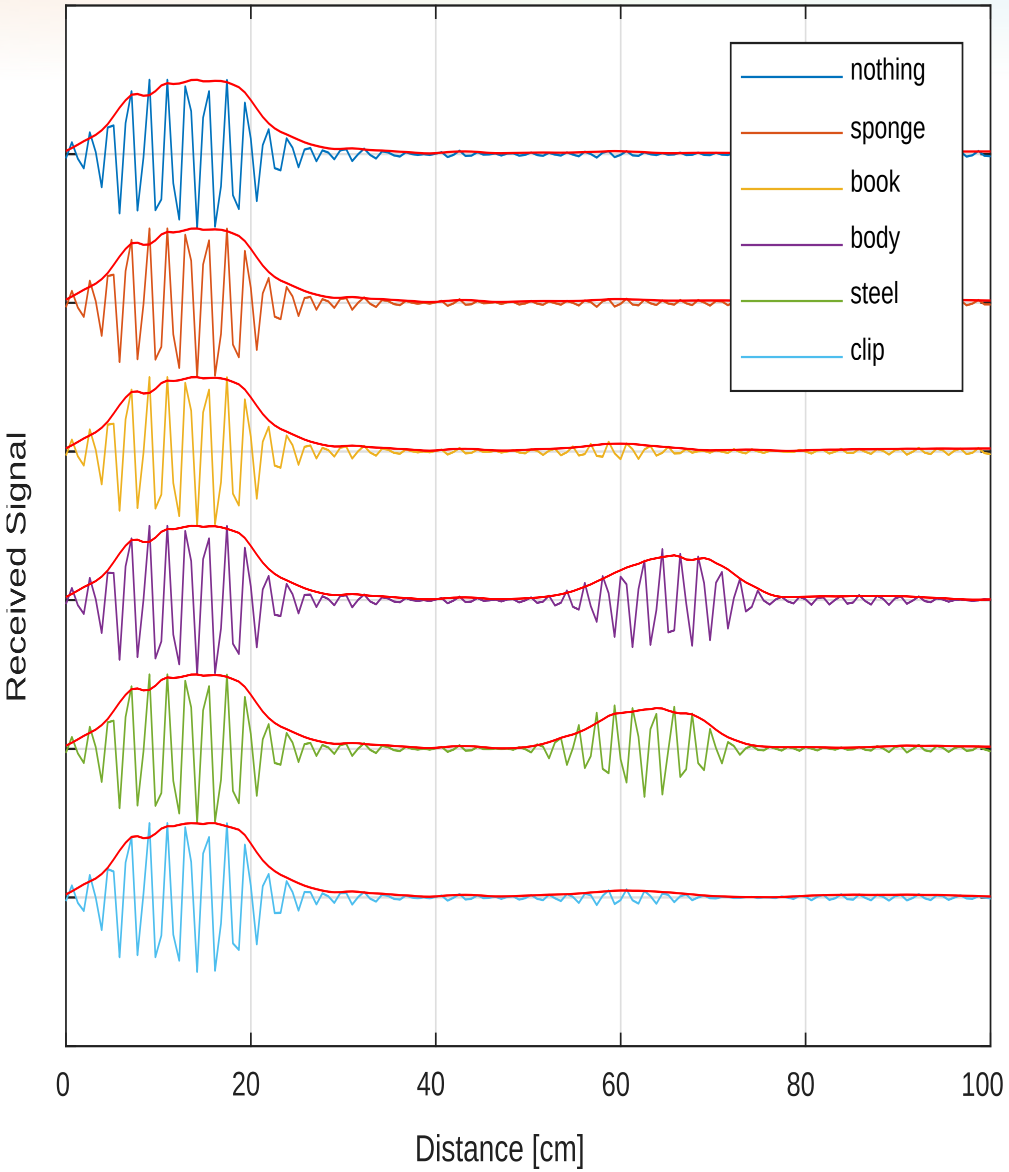
국립전파연구원장 국립전파연구원장인

Director General of National Radio Research Agency

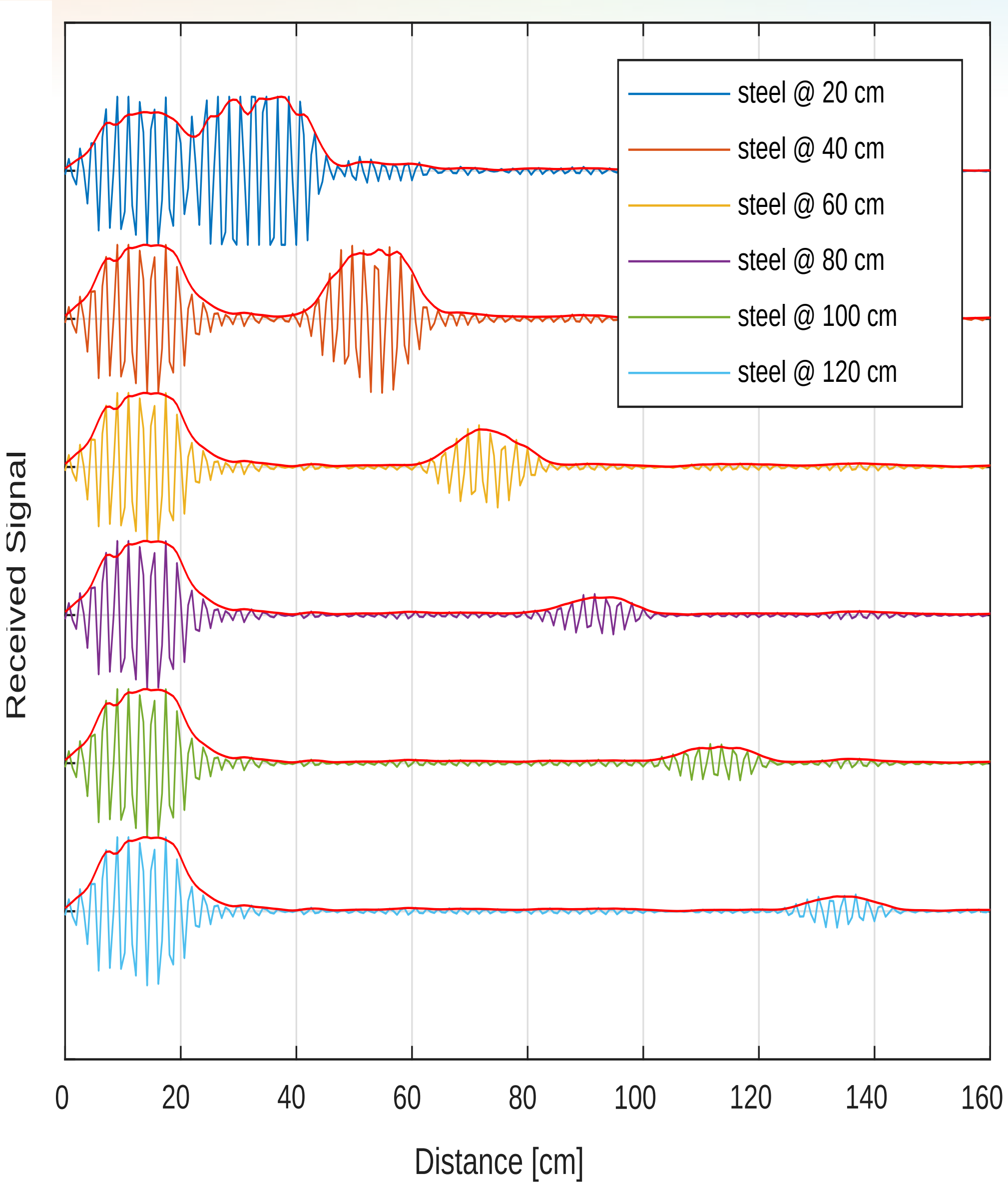
※ 인증 받은 방송통신기자재는 반드시 "적합성평가표시" 를 부착하여 유통하여야 합니다.
위반시 과태료 처분 및 인증이 취소될 수 있습니다.

UWB Radar Signal Analysis with respect to Reflectors



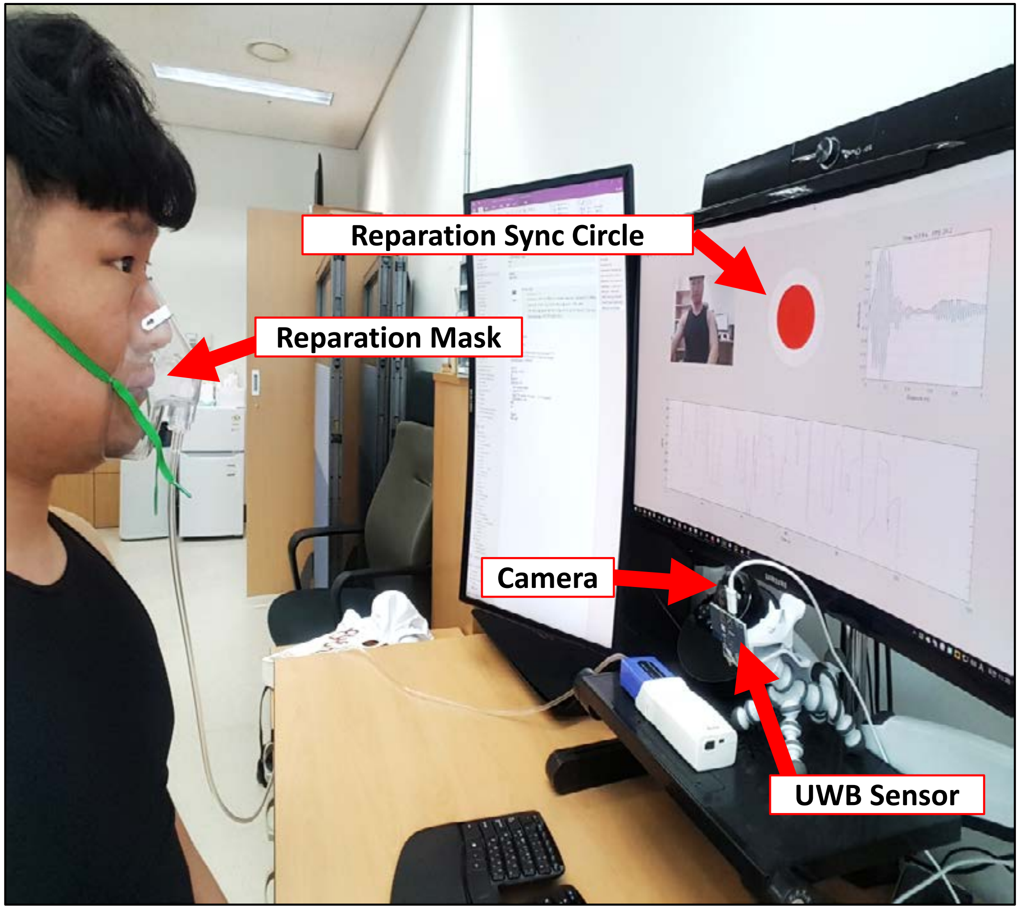


UWB Radar Signal Analysis with respect to Distance

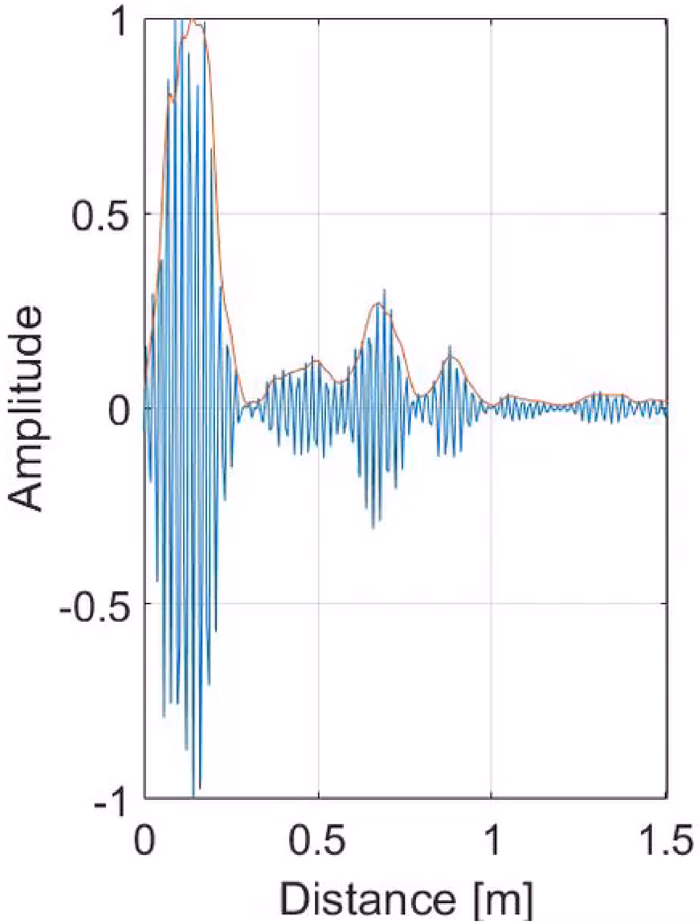


Respiration Detection via UWB Radar in Static Pose

< X4M200 >

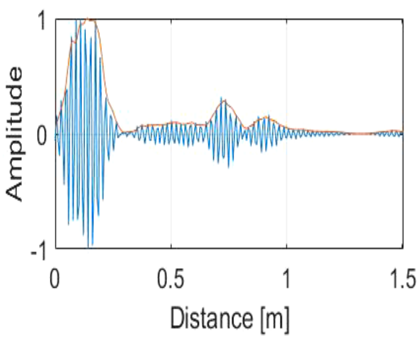


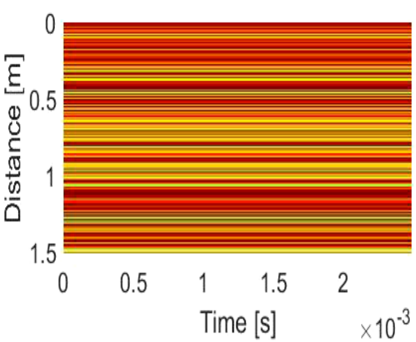
< X4M200 Signal>



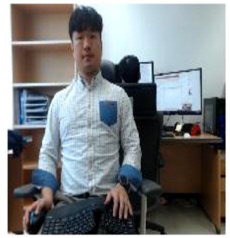
Signals via UWB Radar according to Diverse Poses

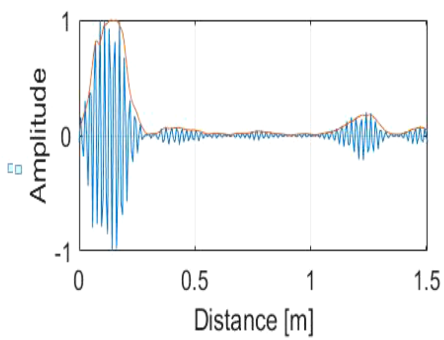
< Near >

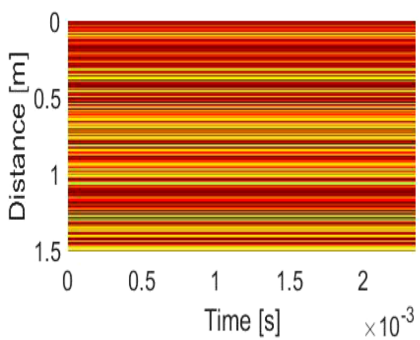




< Far >







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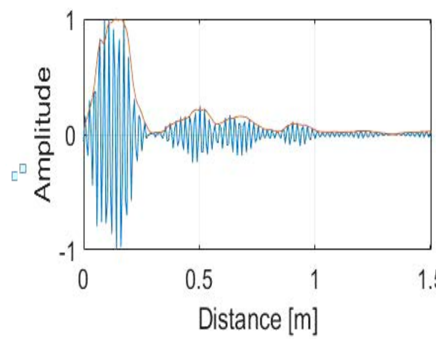

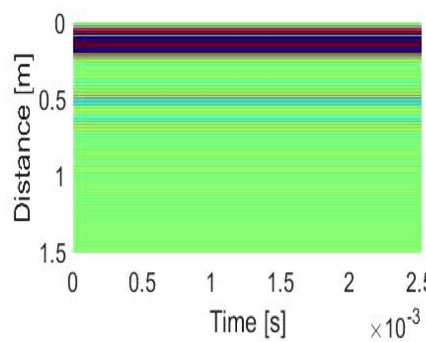

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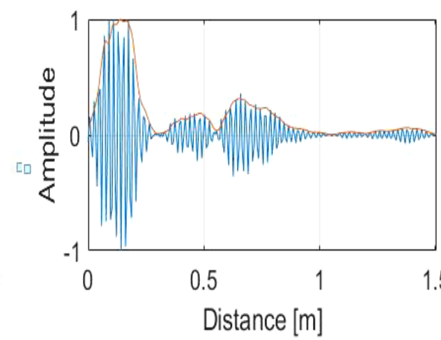
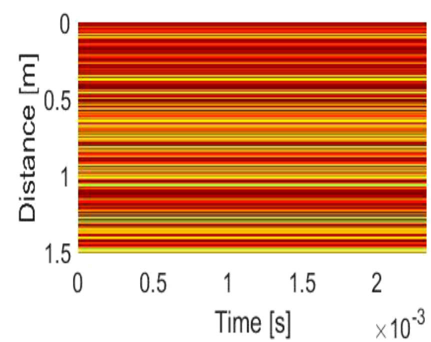


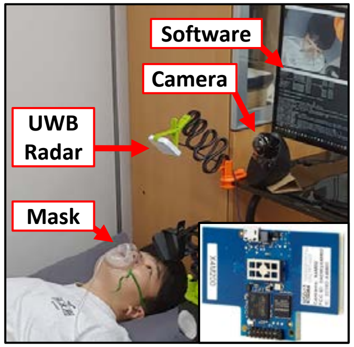


Noncontact Radar Signals & Brain Waves

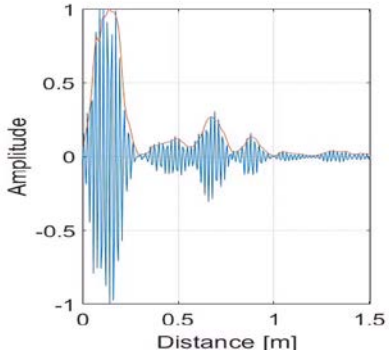
Respiration Monitoring via UWB Radar

- Respiration Pattern were obtained from Mask
- **Ultra-Wide Band Radar was used to measure Body Movement proportional to Respiration**

< Measurement of Mask & UWB >

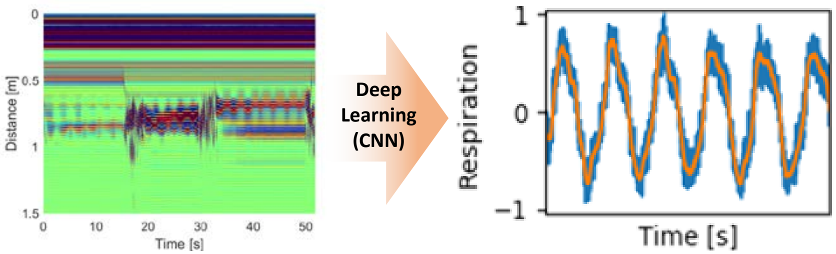


< UWB Signal for Respiration >



✓ **Convolutional Neural Network was used for Prediction of Respiration Pattern from UWB Signals**

< **Input** = Sensor Signals > < **Output** = Respiration Pattern >

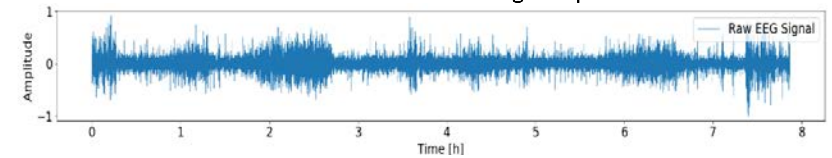


Sleep Scoring based on Brain Waves

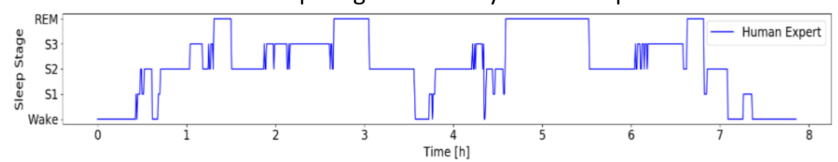
- **Sleep Stage was scored by Human Experts via Polysomnography which is recording Brain waves**

  : EEG, EOG, EMG, ECG, etc.

< Brain Waves during Sleep >

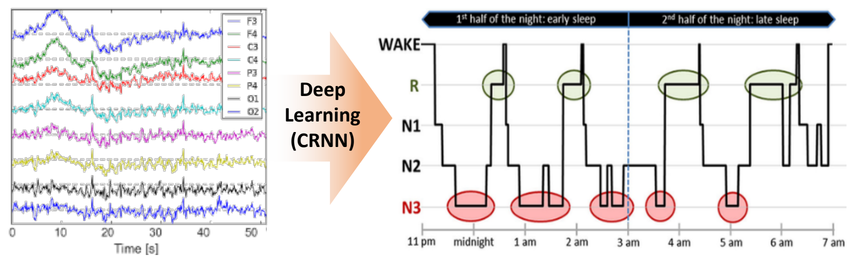


< Sleep Stages scored by Human Expert >

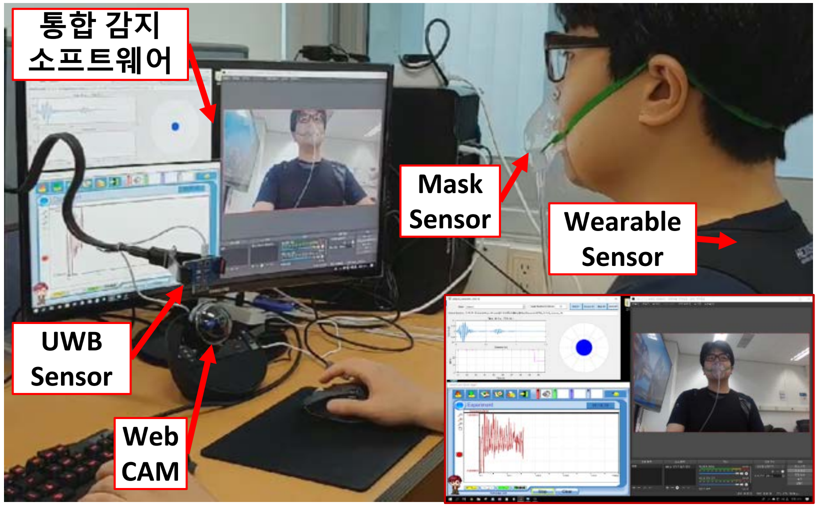


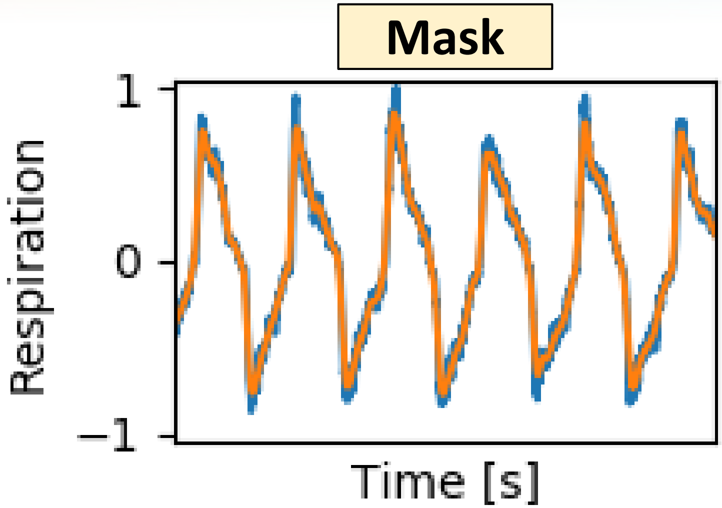
✓ **Convolutional Recurrent Neural Network was used for Sleep Scoring from Single-Channel EEG Signals**

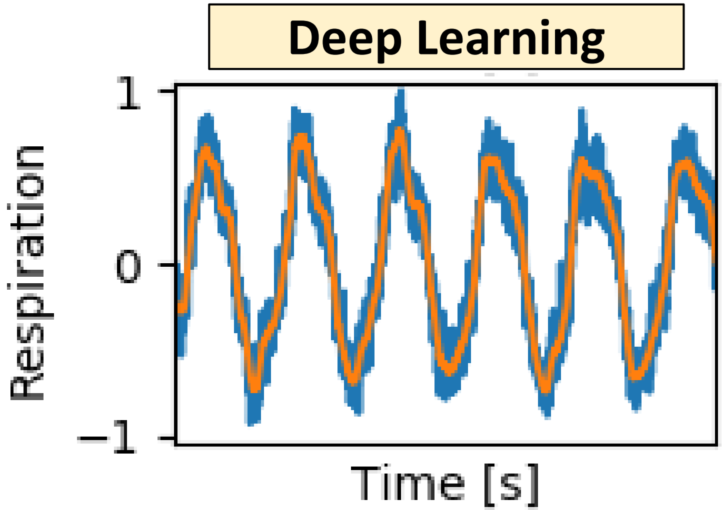
< **Input** = Brain Waves > < **Output** = Sleep Stages >



Deep Learning for Respiration Monitoring via UWB Radar



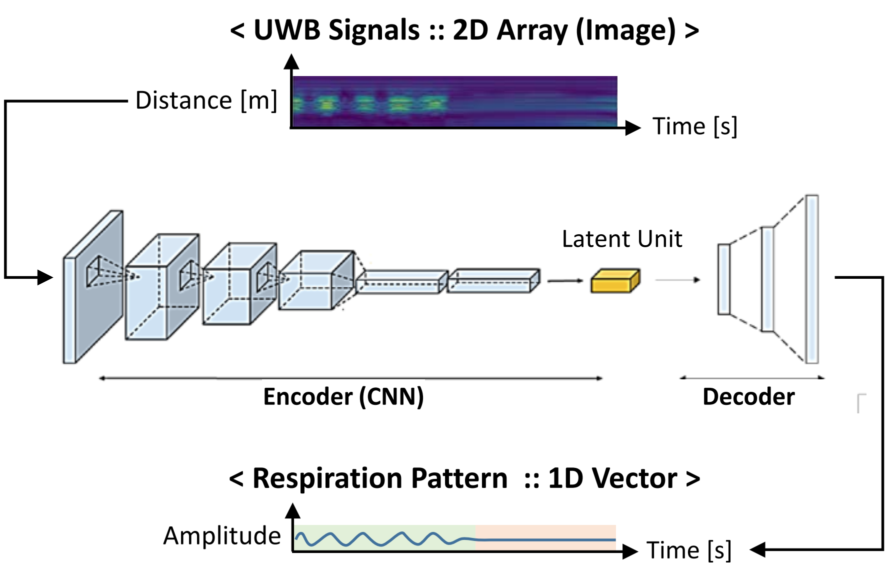


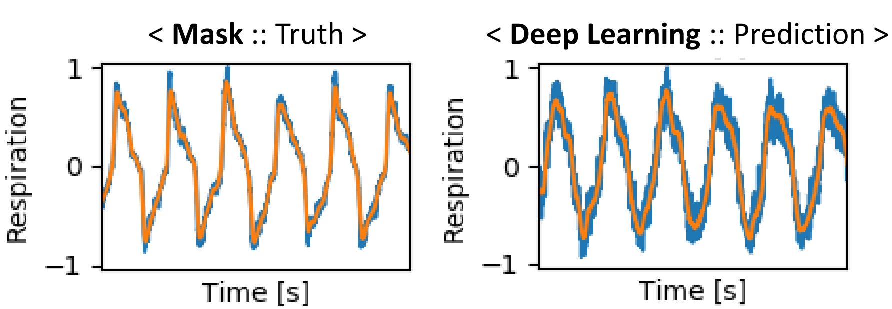


Respiration Monitoring via Noncontact UWB Radar

Prediction of Respiration Pattern

✓ **Convolutional Neural Network was used for Prediction of Respiration Pattern from UWB Signals**

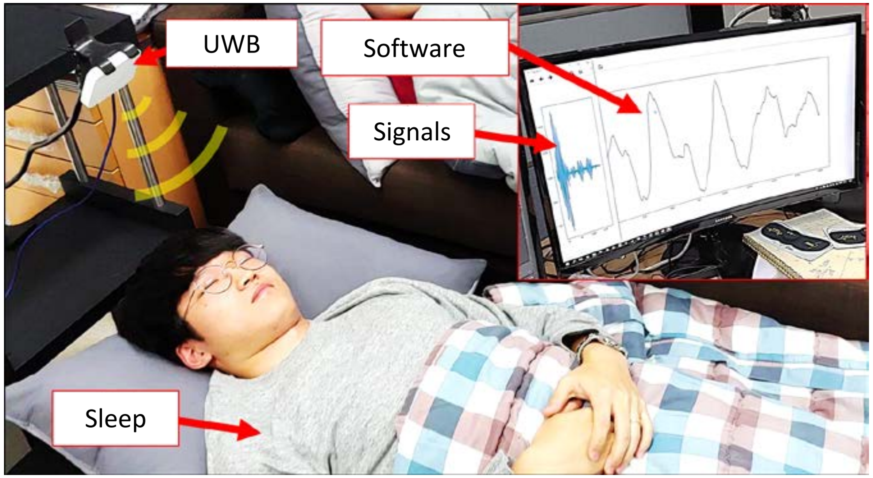


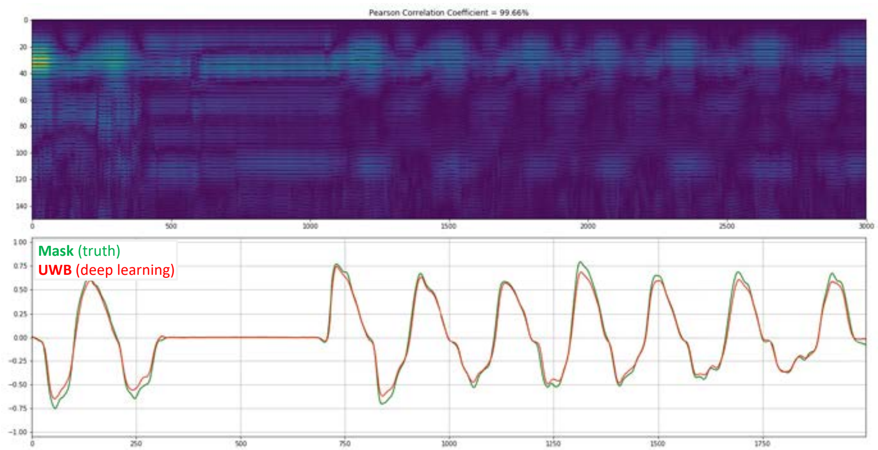


Realtime Respiration Monitoring

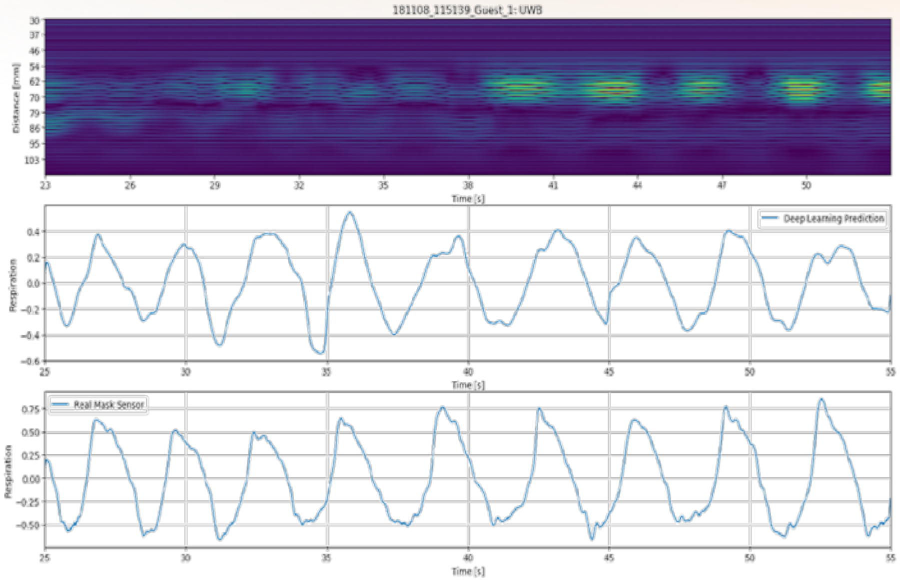
✓ **Pearson Correlation Coefficient was Larger than 95%**

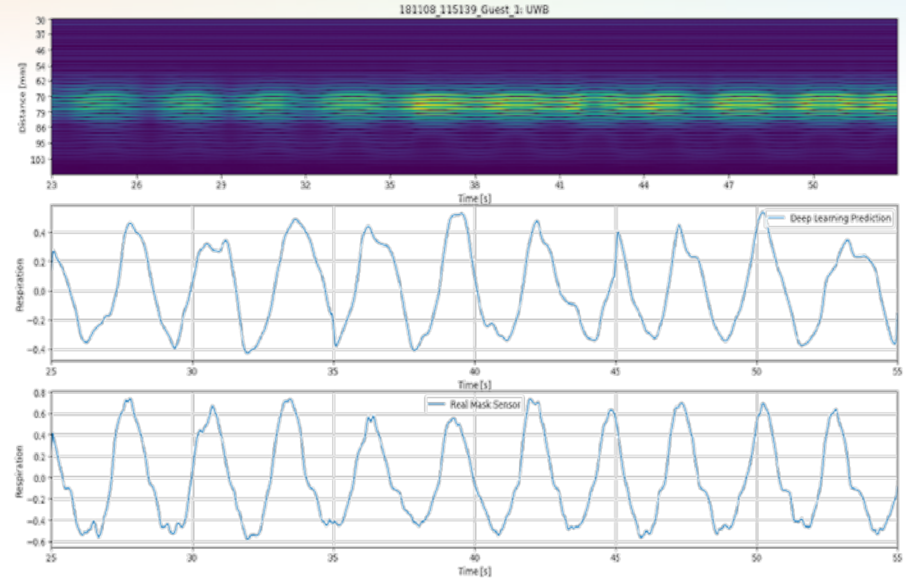
(between Ground Truth and Netork Prediction)

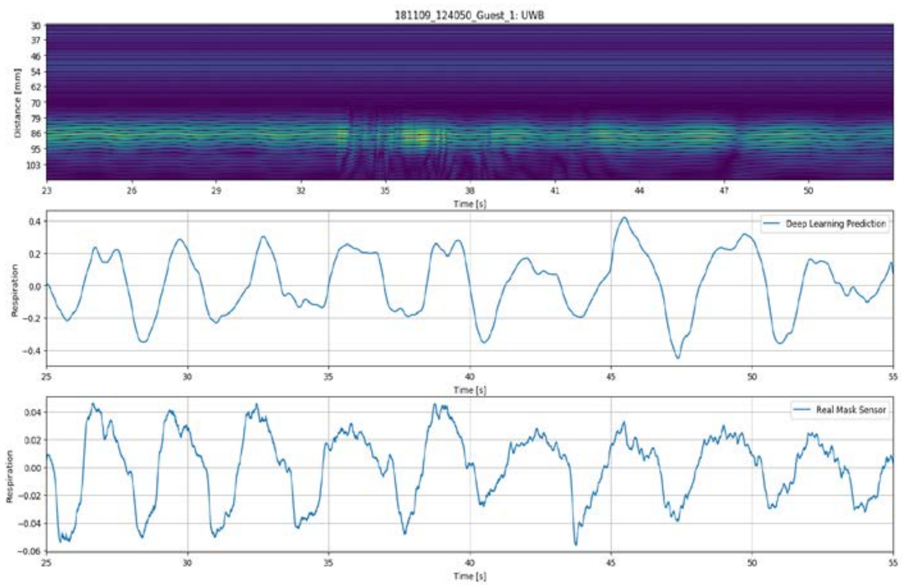


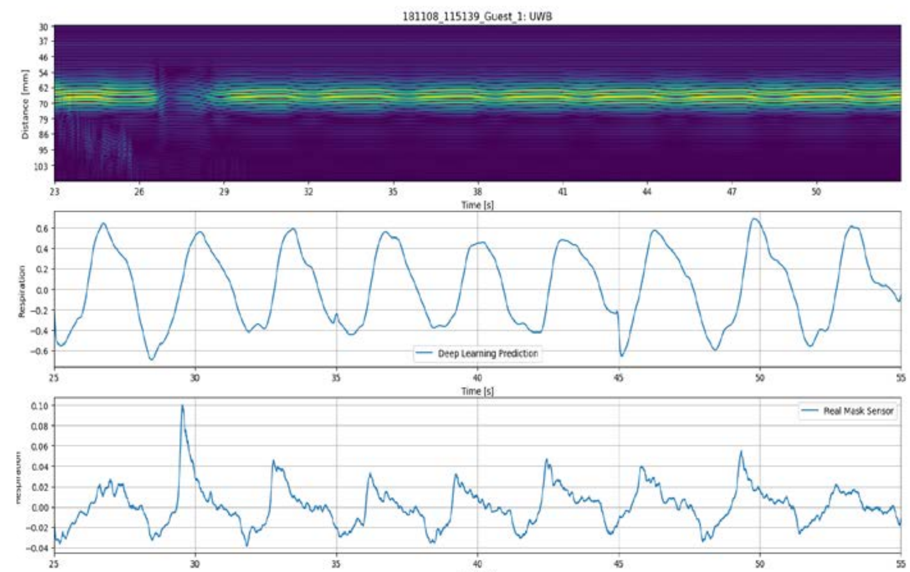


Respiration Monitoring via Noncontact UWB Radar

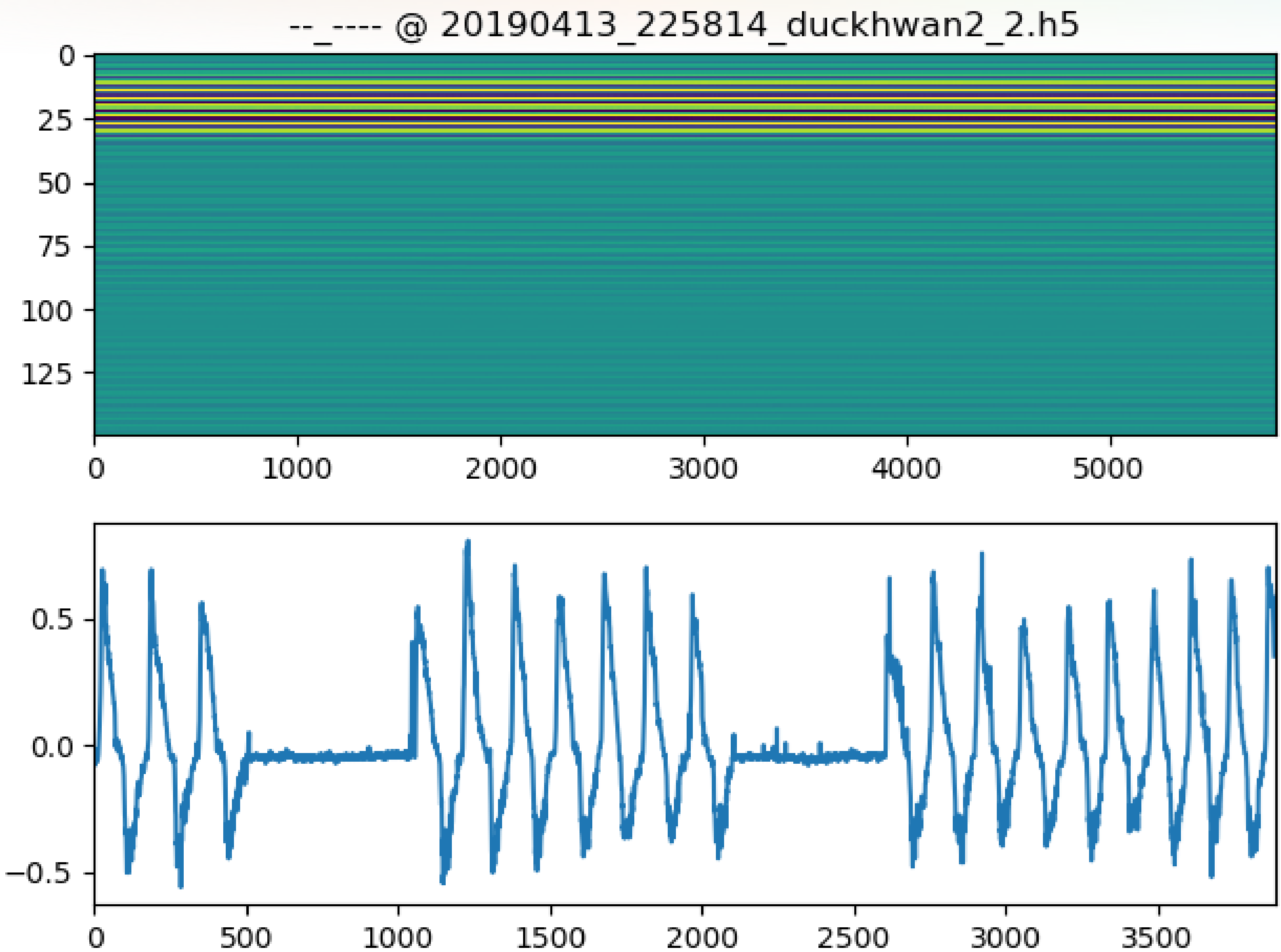








Raw Signals of UWB Radar & Mask Sensor



Preprocesssing was Very Important!!!

- 딥러닝 모델 최적화에 앞서, 입력 데이터의 특성 분석 선행

- 입력 신호의 전처리 조건 (--_----)

  ❖ --: Mask 신호 전처리

  S = Smoothing

  N = Normalization

  ❖ ----: UWB 신호 전처리

  B = Base Subtraction

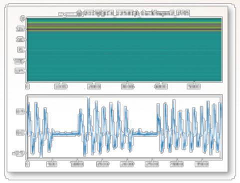
  A = Taking Absolute Values

  2 = 2D Smoothing

  N = Normalization

option	r_mean	abs(r)_mean	option	r_mean	abs(r)_mean
--_----	37.3%	53.5%	----_--	37.30%	53.46%
--_-A--	16.6%	48.3%	----_-N	26.21%	54.88%
--_-A-N	28.4%	46.0%	----_S-	29.18%	54.94%
--_B---	55.9%	61.2%	----_SN	34.79%	57.18%
--_B--N	52.2%	60.7%	-A--_--	16.61%	48.28%
--_BA--	58.0%	63.7%	-A--_-N	29.12%	52.69%
--_BA-N	54.5%	59.9%	-A--_S-	30.75%	50.40%
--_BA2-	12.9%	41.0%	-A--_SN	31.17%	53.60%
--_BA2N	11.7%	43.2%	-A-N_--	28.35%	46.01%
-N_----	26.2%	54.9%	-A-N_-N	21.98%	49.76%
-N_-A--	29.1%	52.7%	-A-N_S-	25.50%	51.60%
-N_-A-N	22.0%	49.8%	-A-N_SN	23.70%	49.97%
-N_B---	56.0%	61.4%	B---_--	55.93%	61.21%
-N_B--N	52.3%	60.2%	B---_-N	55.99%	61.42%
-N_BA--	58.3%	64.0%	B---_S-	58.63%	65.18%
-N_BA-N	52.6%	59.0%	B---_SN	60.04%	66.29%
-N_BA2-	14.9%	43.6%	BA--_--	58.02%	63.74%
-N_BA2N	14.5%	45.0%	BA--_-N	58.27%	64.04%
S-_----	29.2%	54.9%	BA--_S-	60.81%	66.78%
S-_-A--	30.7%	50.4%	BA--_SN	60.36%	67.41%
S-_-A-N	25.5%	51.6%	BA2-_--	12.94%	40.98%
S-_B---	58.6%	65.2%	BA2-_-N	14.91%	43.57%
S-_B--N	53.0%	61.0%	BA2-_S-	12.23%	42.02%
S-_BA--	60.8%	66.8%	BA2-_SN	8.99%	41.10%
S-_BA-N	52.9%	60.2%	BA2N_--	11.68%	43.15%
S-_BA2-	12.2%	42.0%	BA2N_-N	14.48%	45.00%
S-_BA2N	13.9%	42.9%	BA2N_S-	13.89%	42.95%
SN_----	34.8%	57.2%	BA2N_SN	20.18%	46.30%
SN_-A--	31.2%	53.6%	BA-N_--	54.53%	59.90%
SN_-A-N	23.7%	50.0%	BA-N_-N	52.61%	58.95%
SN_B---	60.0%	66.3%	BA-N_S-	52.92%	60.16%
SN_B--N	53.8%	62.7%	BA-N_SN	59.95%	65.68%
SN_BA--	60.4%	67.4%	B--N_--	52.22%	60.69%
SN_BA-N	60.0%	65.7%	B--N_-N	52.34%	60.24%
SN_BA2-	9.0%	41.1%	B--N_S-	53.04%	60.95%
SN_BA2N	20.2%	46.3%	B--N_SN	53.82%	62.66%

Preprocesssing was Very Important!!!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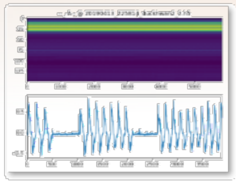
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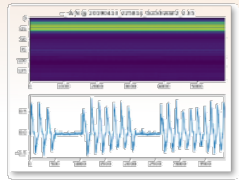
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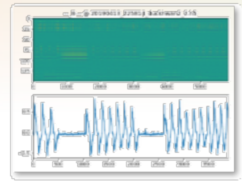
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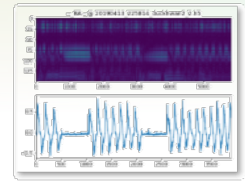
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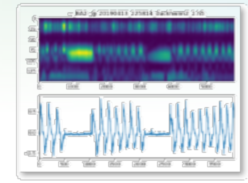
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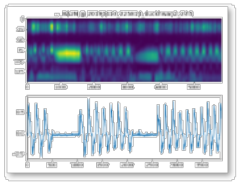
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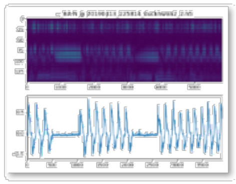
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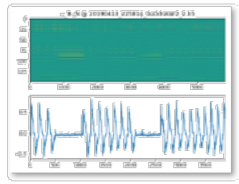
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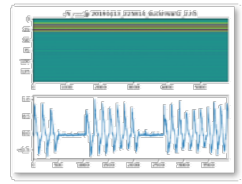
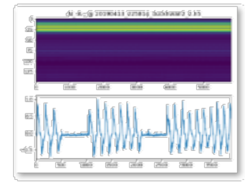

-N_----.png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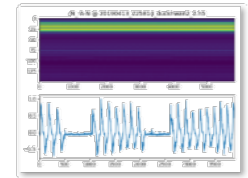
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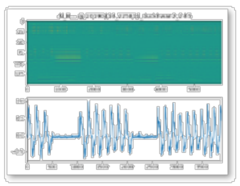
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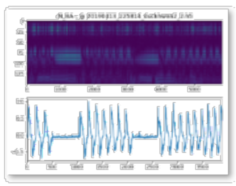
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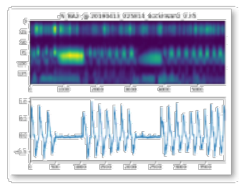
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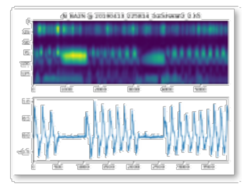
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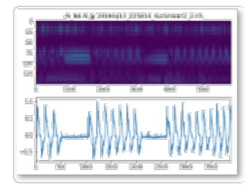
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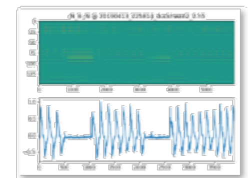
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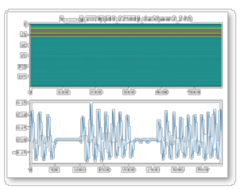
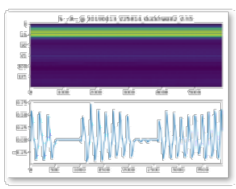

S-_----.png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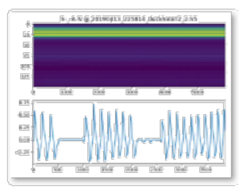
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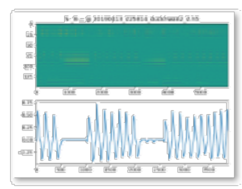
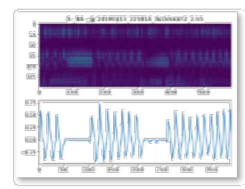

S-_B---.png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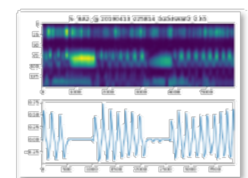
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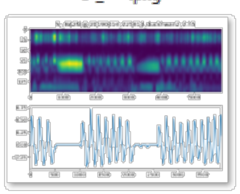
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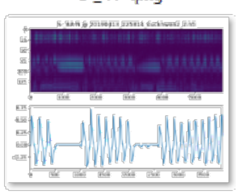
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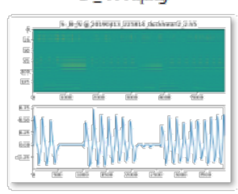
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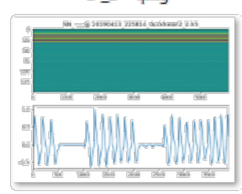
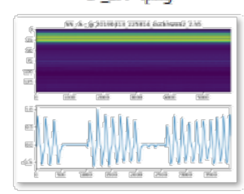

SN_----.png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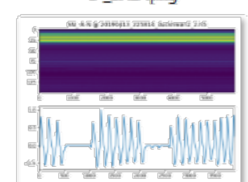
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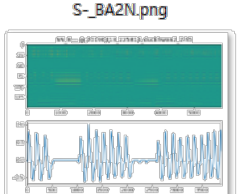
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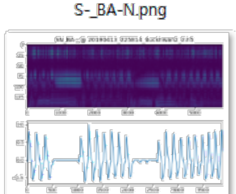
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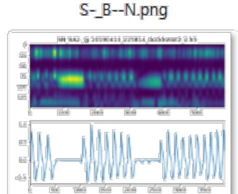
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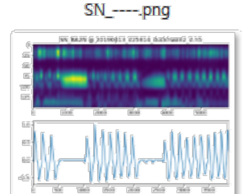
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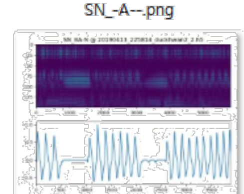
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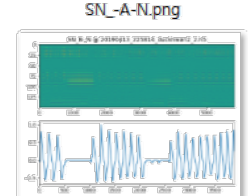
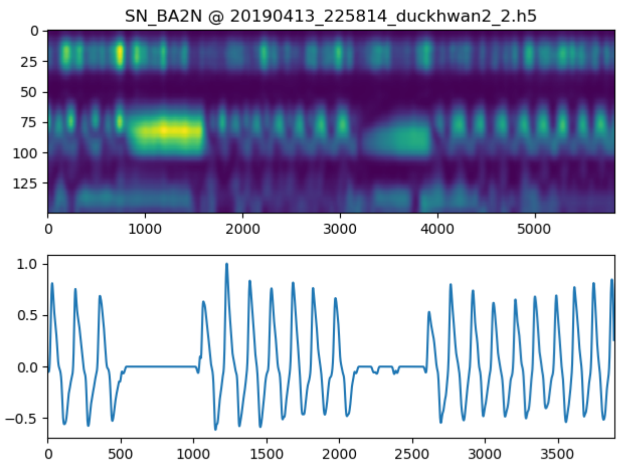
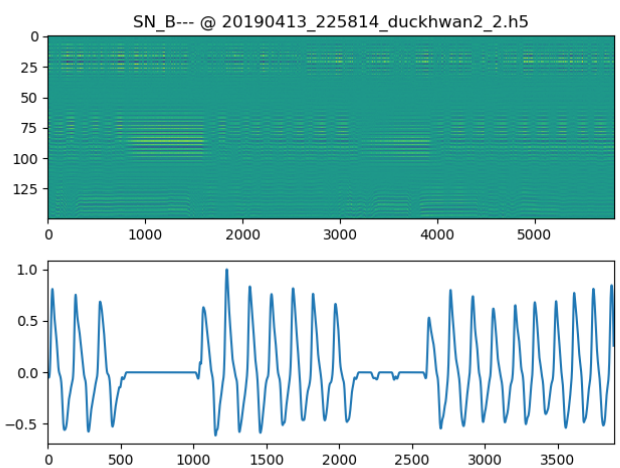

SN_B--N.png

Preprocesssing was Very Important!!!

option	r_mean	abs(r)_mean
BA2N_SN	20.18%	46.30%



option	r_mean	abs(r)_mean
SN_B---	60.0%	66.3%

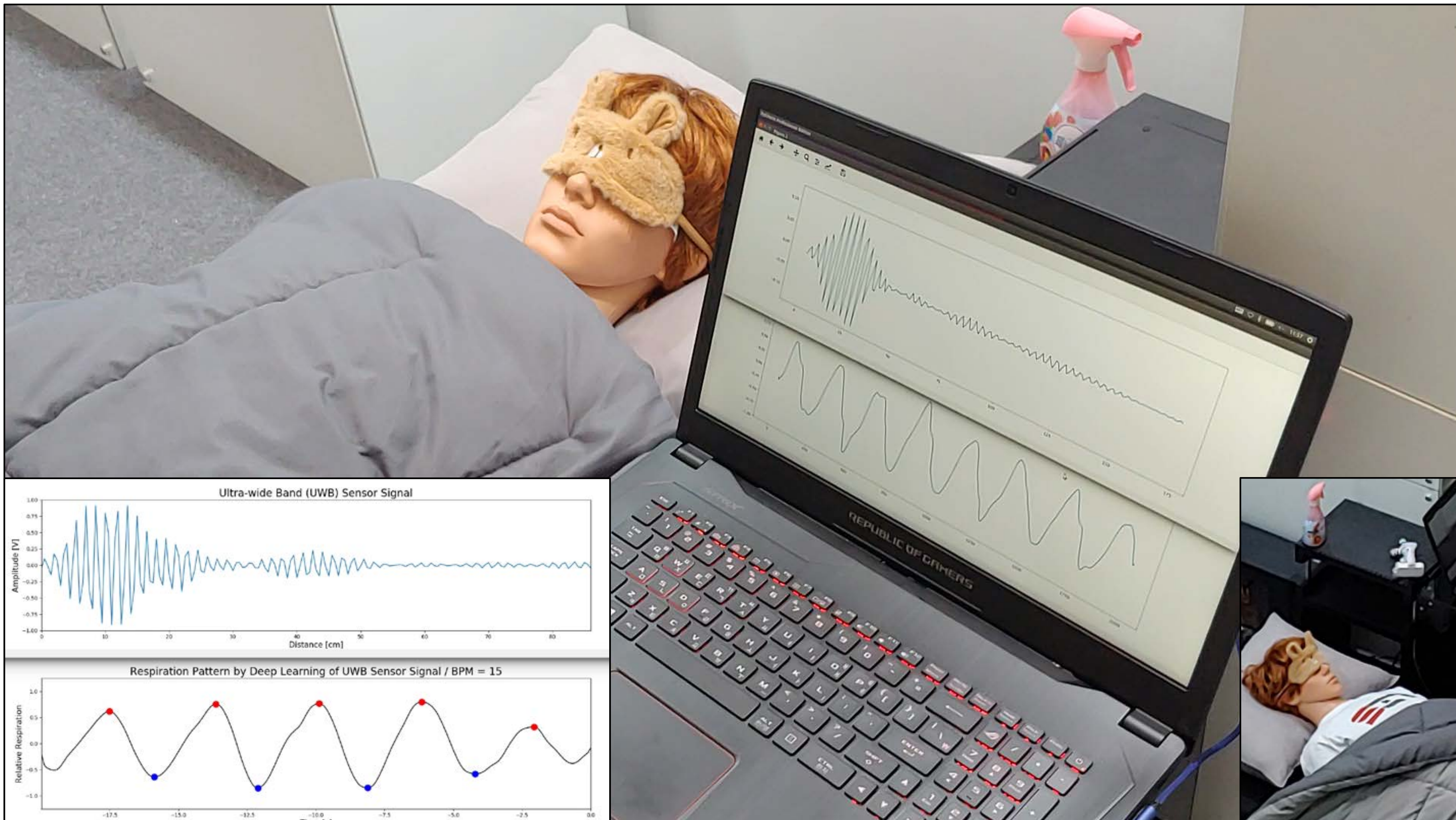


option	r_mean	abs(r)_mean	option	r_mean	abs(r)_mean
--_----	37.3%	53.5%	----_--	37.30%	53.46%
--_-A--	16.6%	48.3%	----_-N	26.21%	54.88%
--_-A-N	28.4%	46.0%	----_S-	29.18%	54.94%
--_B---	55.9%	61.2%	----_SN	34.79%	57.18%
--_B--N	52.2%	60.7%	-A--_--	16.61%	48.28%
--_BA--	58.0%	63.7%	-A--_-N	29.12%	52.69%
--_BA-N	54.5%	59.9%	-A--_S-	30.75%	50.40%
--_BA2-	12.9%	41.0%	-A--_SN	31.17%	53.60%
--_BA2N	11.7%	43.2%	-A-N_--	28.35%	46.01%
-N_----	26.2%	54.9%	-A-N_-N	21.98%	49.76%
-N_-A--	29.1%	52.7%	-A-N_S-	25.50%	51.60%
-N_-A-N	22.0%	49.8%	-A-N_SN	23.70%	49.97%
-N_B---	56.0%	61.4%	B---_--	55.93%	61.21%
-N_B--N	52.3%	60.2%	B---_-N	55.99%	61.42%
-N_BA--	58.3%	64.0%	B---_S-	58.63%	65.18%
-N_BA-N	52.6%	59.0%	B---_SN	60.04%	66.29%
-N_BA2-	14.9%	43.6%	BA--_--	58.02%	63.74%
-N_BA2N	14.5%	45.0%	BA--_-N	58.27%	64.04%
S-_----	29.2%	54.9%	BA--_S-	60.81%	66.78%
S-_-A--	30.7%	50.4%	BA--_SN	60.36%	67.41%
S-_-A-N	25.5%	51.6%	BA2-_--	12.94%	40.98%
S-_B---	58.6%	65.2%	BA2-_-N	14.91%	43.57%
S-_B--N	53.0%	61.0%	BA2-_S-	12.23%	42.02%
S-_BA--	60.8%	66.8%	BA2-_SN	8.99%	41.10%
S-_BA-N	52.9%	60.2%	BA2N_--	11.68%	43.15%
S-_BA2-	12.2%	42.0%	BA2N_-N	14.48%	45.00%
S-_BA2N	13.9%	42.9%	BA2N_S-	13.89%	42.95%
SN_----	34.8%	57.2%	BA2N_SN	20.18%	46.30%
SN_-A--	31.2%	53.6%	BA-N_--	54.53%	59.90%
SN_-A-N	23.7%	50.0%	BA-N_-N	52.61%	58.95%
SN_B---	60.0%	66.3%	BA-N_S-	52.92%	60.16%
SN_B--N	53.8%	62.7%	BA-N_SN	59.95%	65.68%
SN_BA--	60.4%	67.4%	B--N_--	52.22%	60.69%
SN_BA-N	60.0%	65.7%	B--N_-N	52.34%	60.24%
SN_BA2-	9.0%	41.1%	B--N_S-	53.04%	60.95%
SN_BA2N	20.2%	46.3%	B--N_SN	53.82%	62.66%

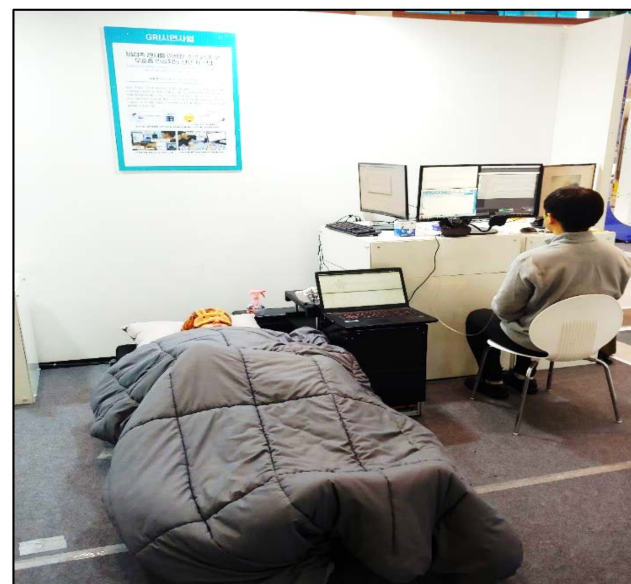
Respiration Monitoring via Noncontact UWB Radar

실시간 UWB 신호 딥러닝 기반 비접촉 호흡 측정 시스템 개발

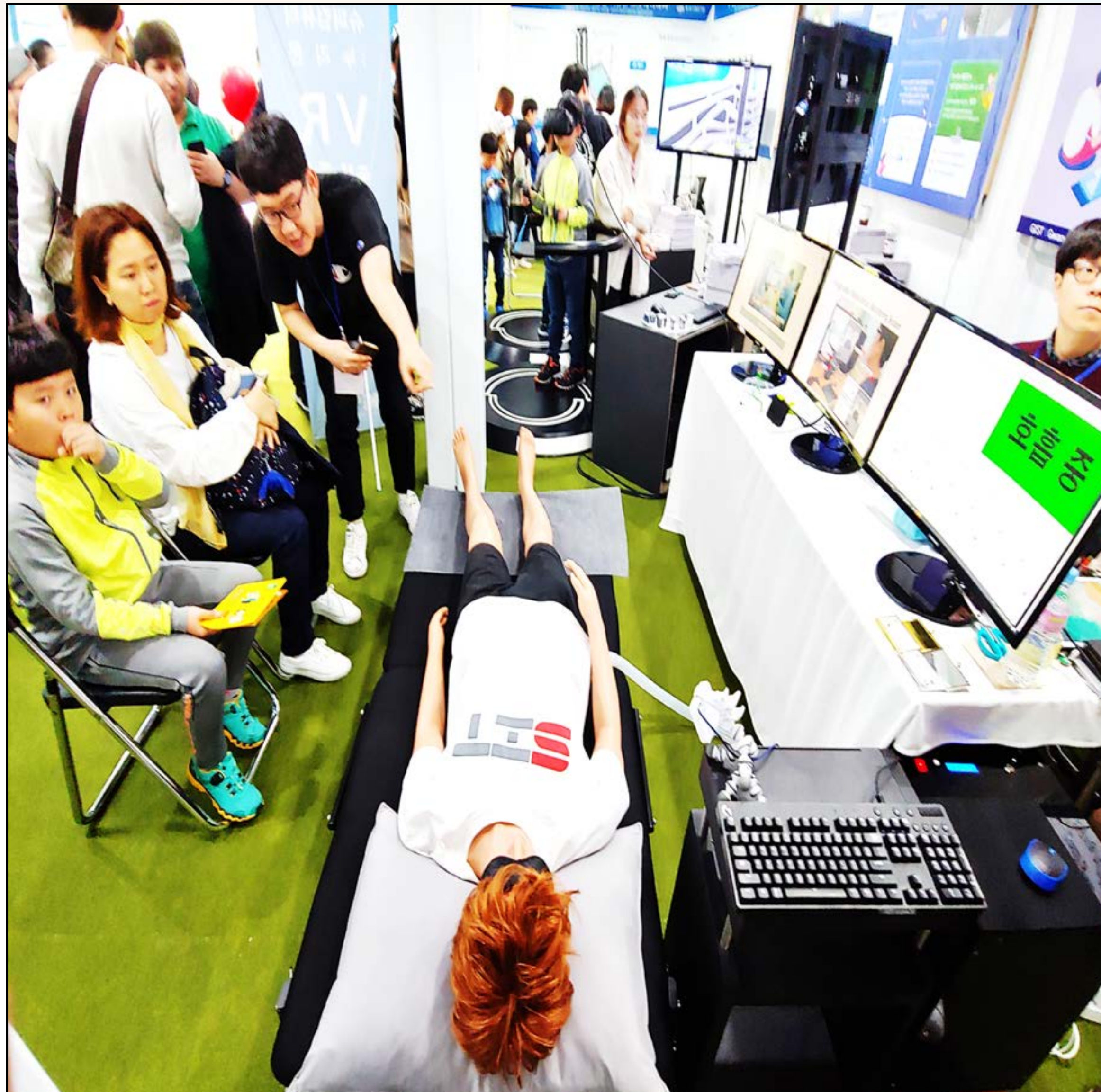
- 호흡 모사 시뮬레이터에 대한 실시간 데이터셋 취득 및 딥러닝 알고리즘 평가



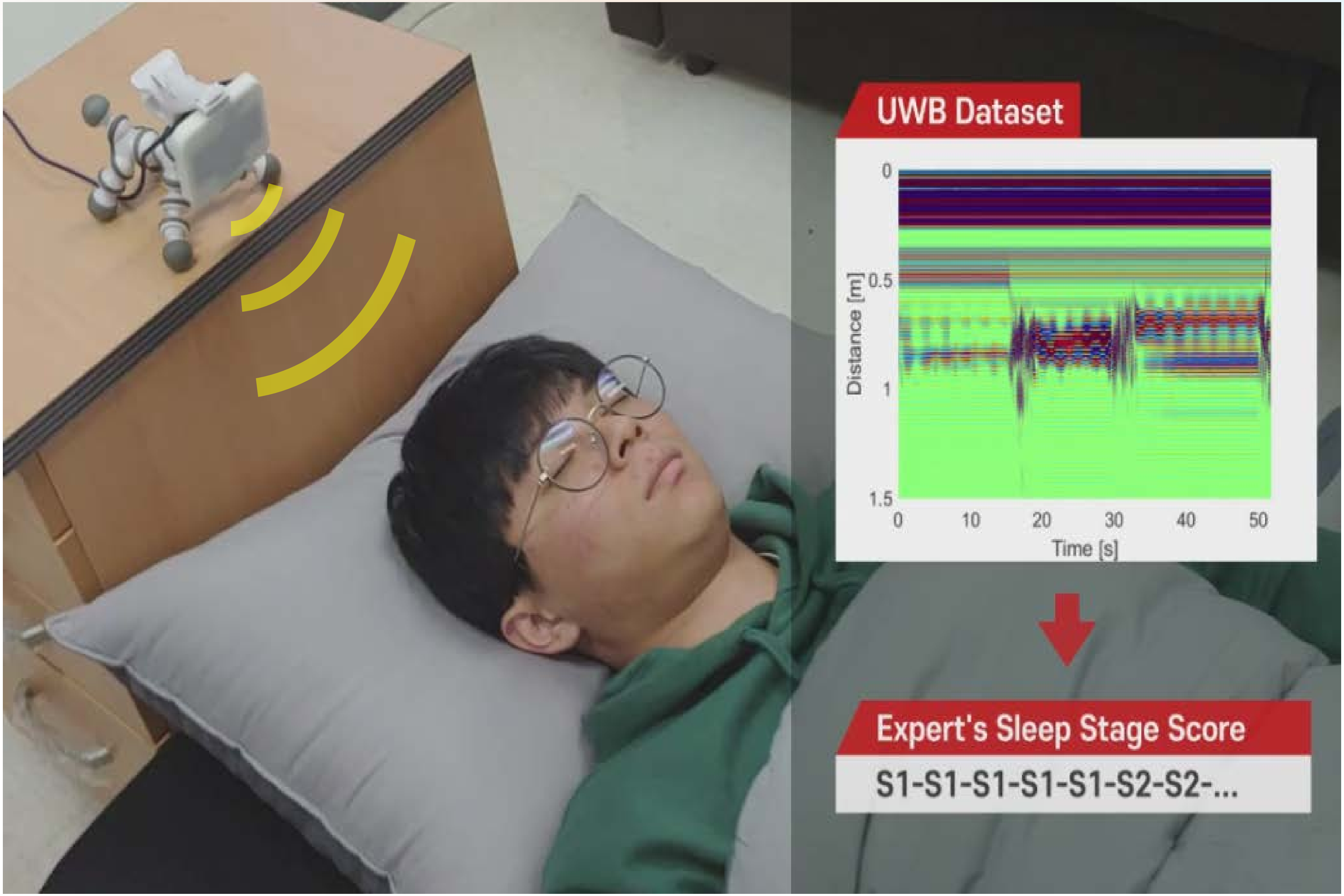
GIST AI Day & GIST 25th Anniversary R&D Exhibition



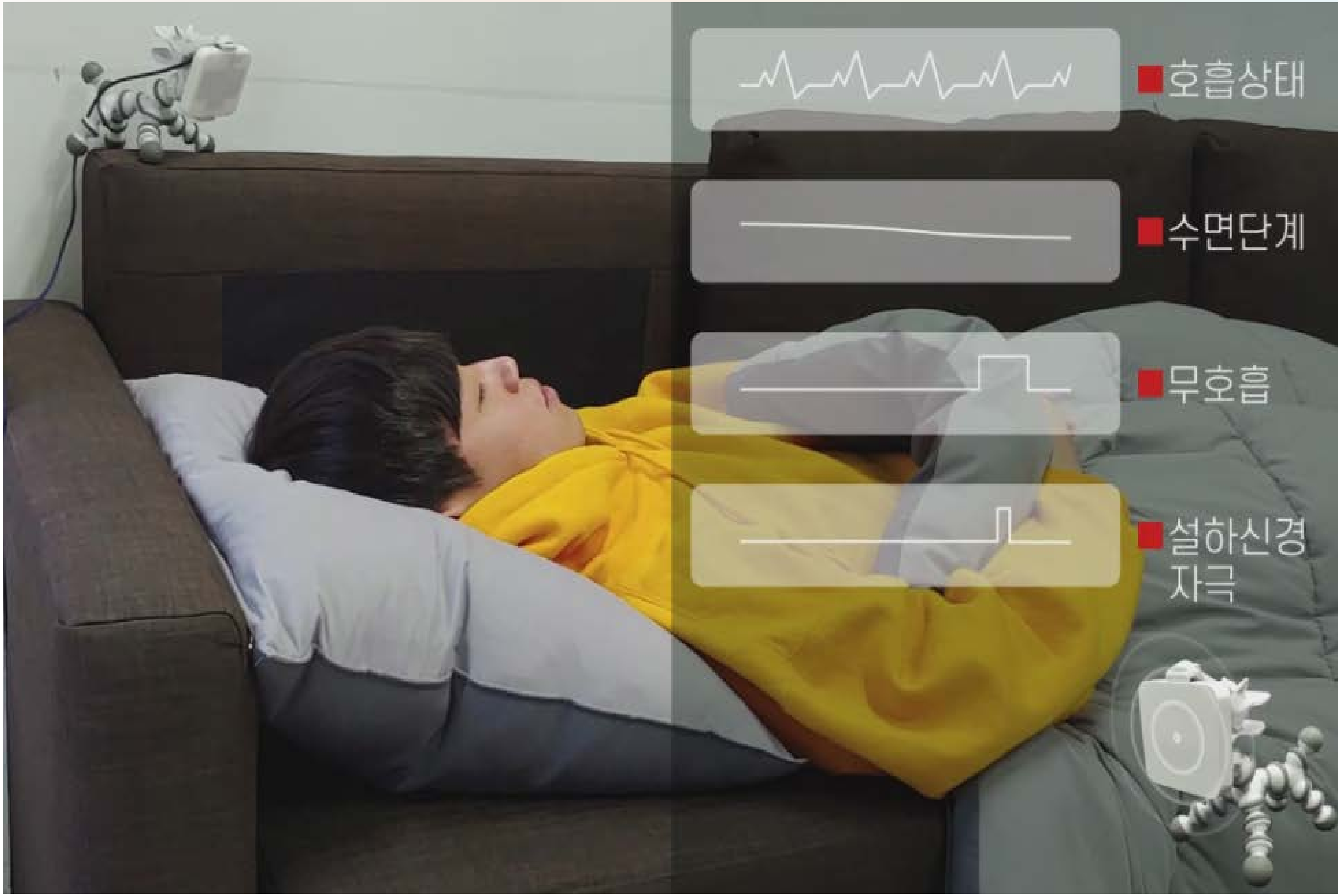
2019 Korea Science Festival @ Seoul City Hall



Sleep Stage Scoring via UWB Data Deep Learning



Non-invasive Apnea Treatment via UWB

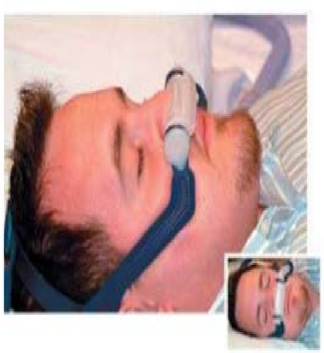


Non-invasive Apnea Treatment via UWB

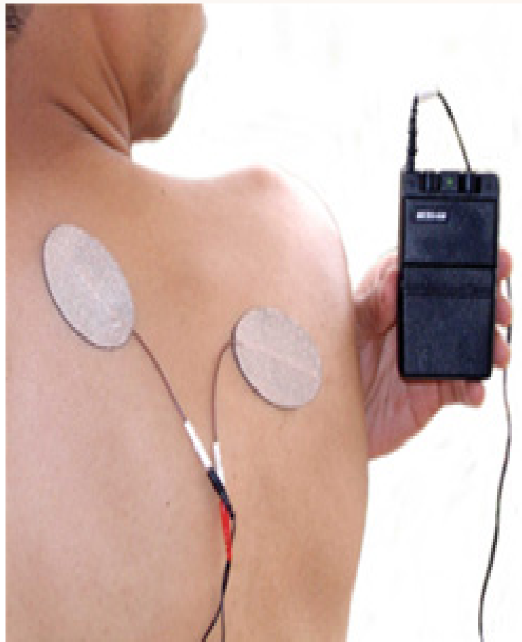
< Full Face Mask >

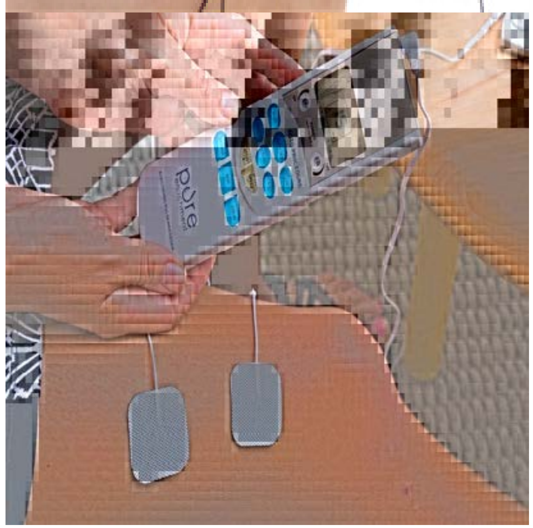
< Nasal Mask >

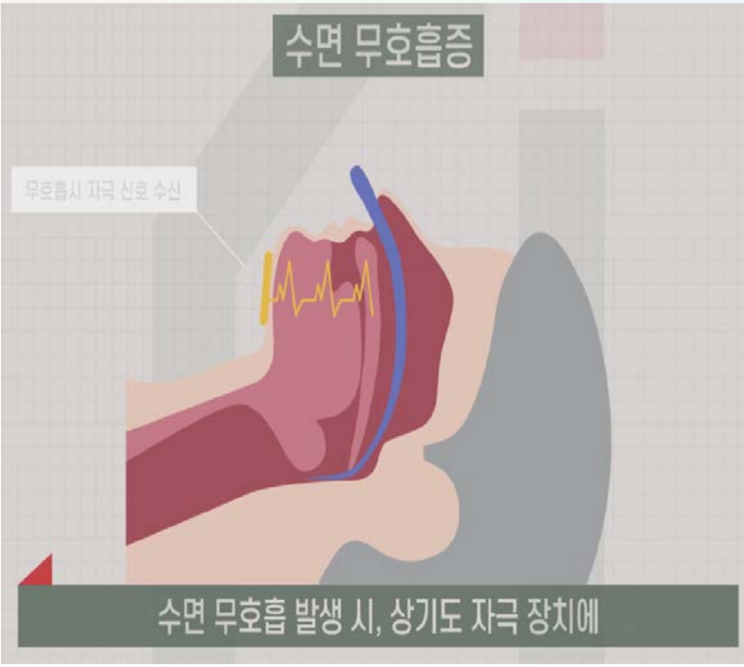
< Nasal Insert >

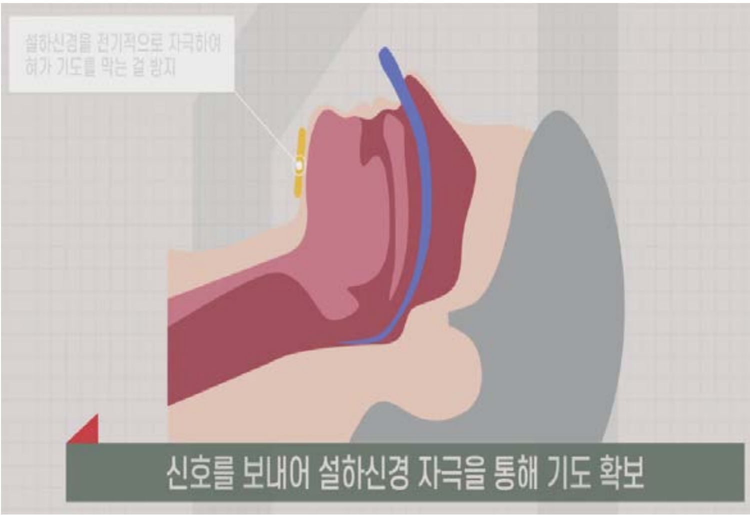


< Transcutaneous electrical nerve stimulation (TENS)>

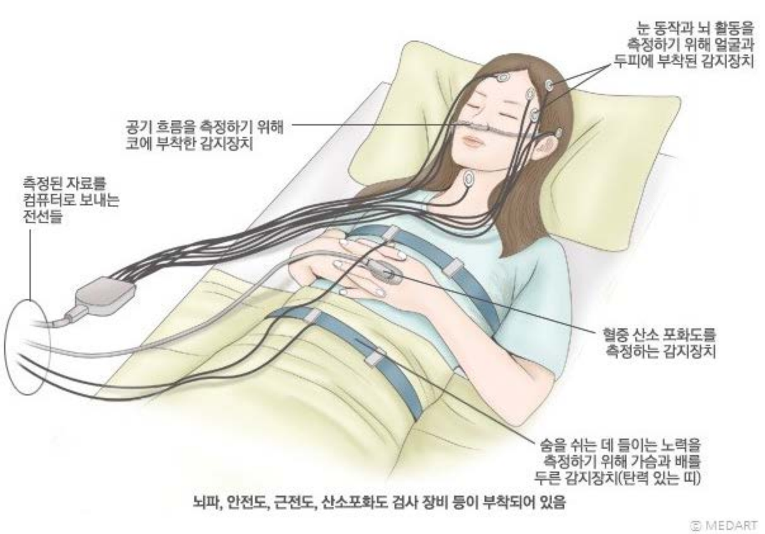


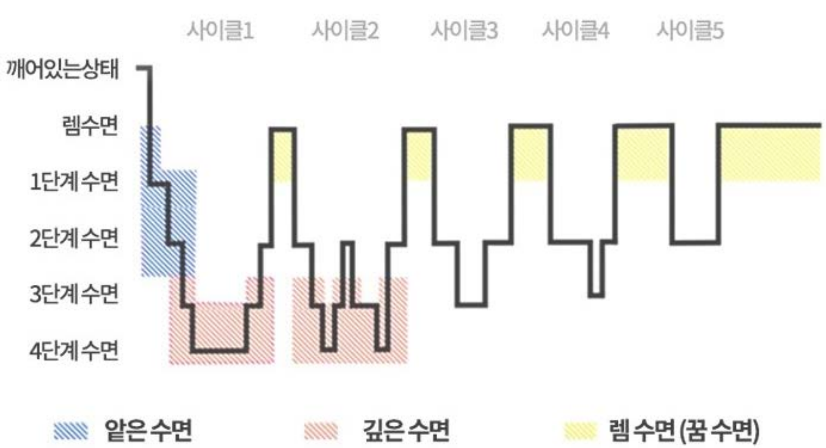


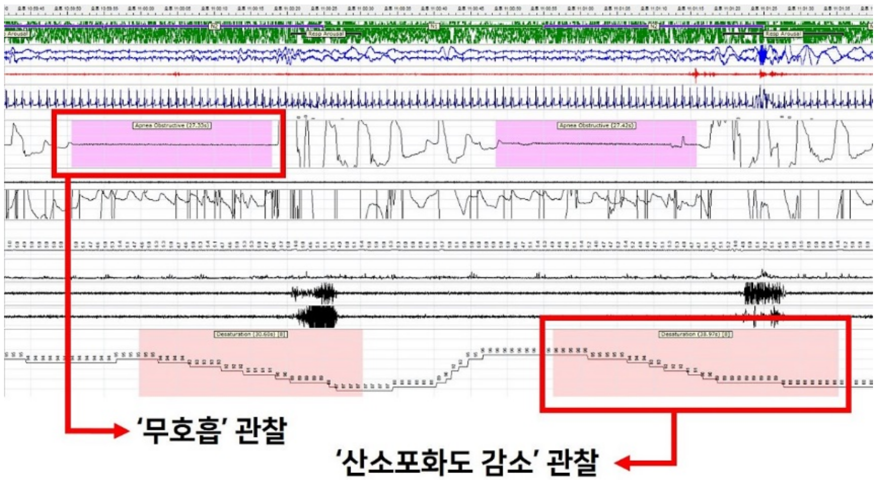




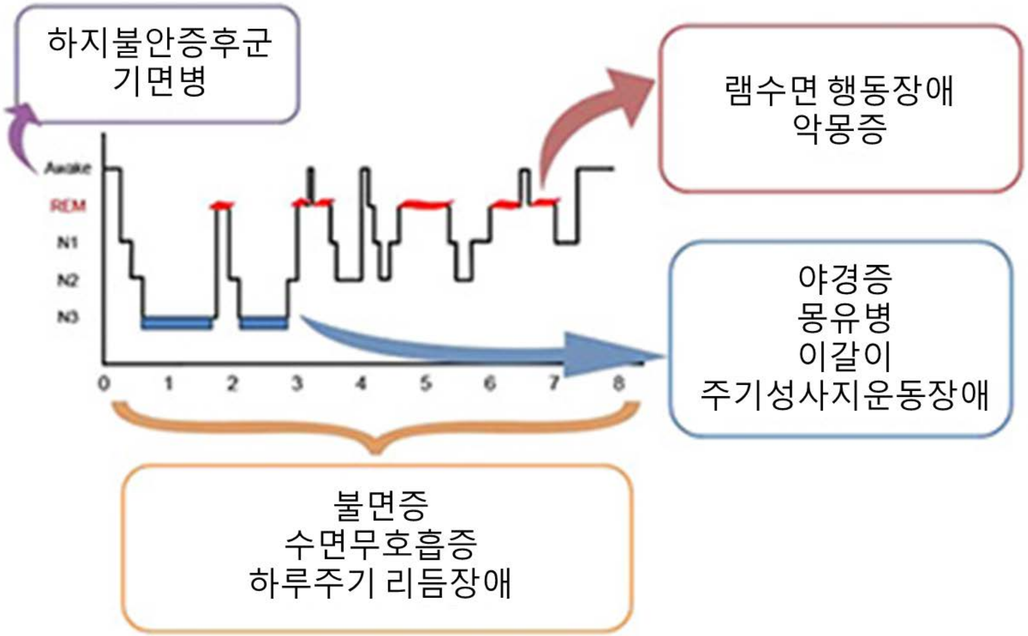
Polysomnography (PSG)





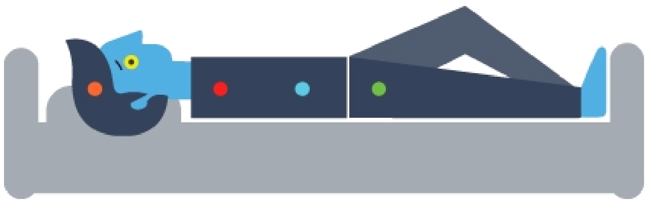


Health Problems according to Sleep Disorder



수면장애가 건강에 미치는 영향

HiDoc



뇌/신경 질환

수면 부족, 피로, 스트레스, 우울증, 불안, 초조감, 기억력/집중력 저하, 면역력 저하, 뇌 회백질 감소로 인한 치매 자극, 두통, 안구충혈

심혈관/내분비 질환

협심증, 고혈압, 심근경색, 호르몬 불균형, 성장 장애, 당뇨병

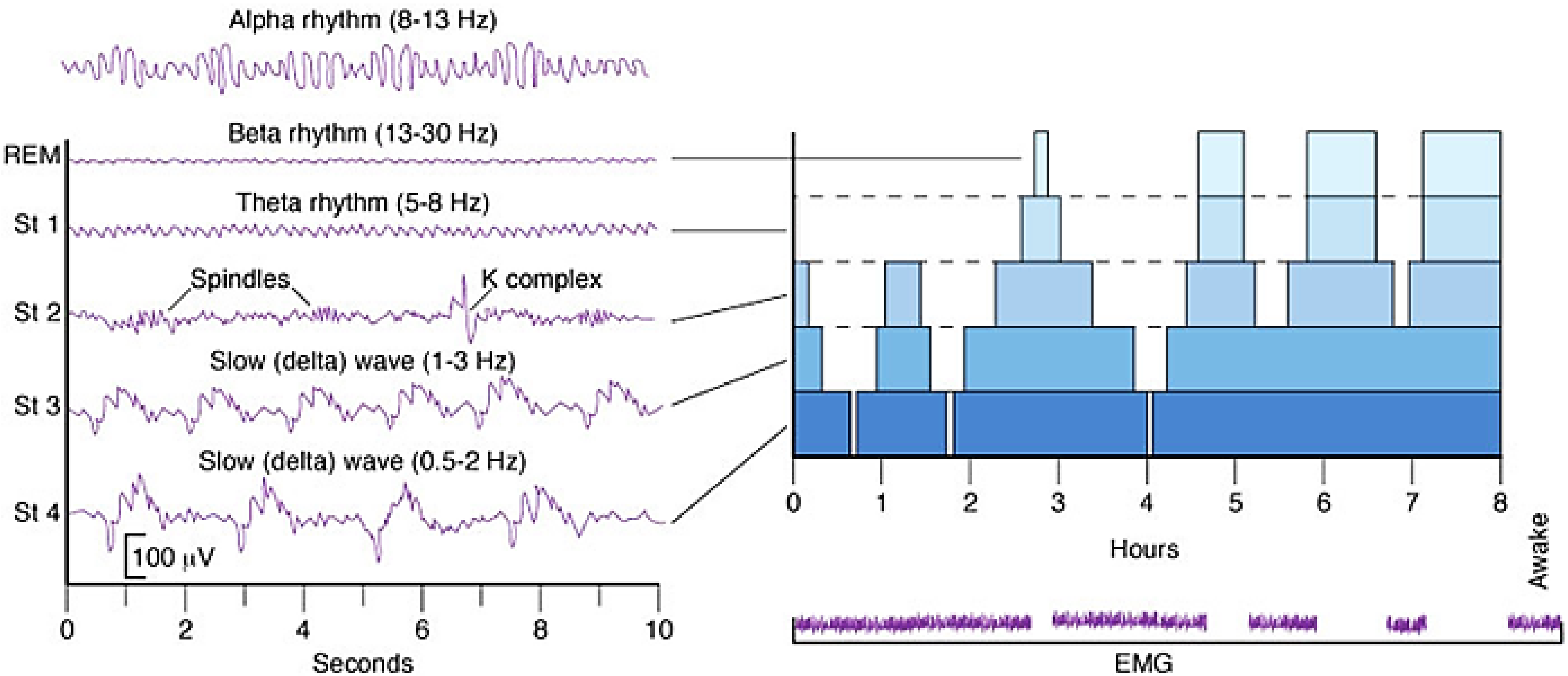
소화기 질환

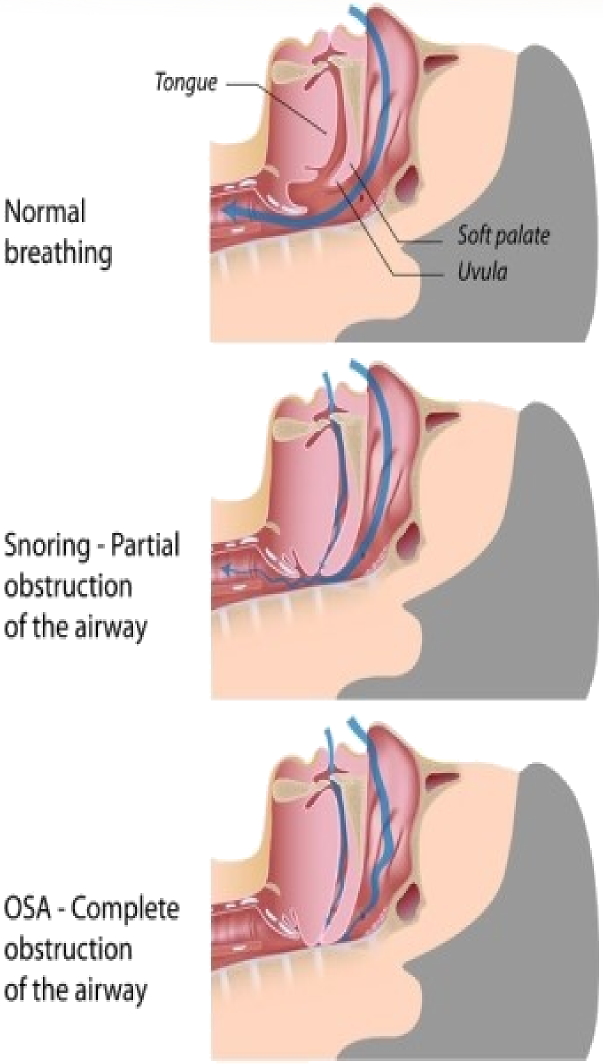
소화불량, 속쓰림, 복부통증, 헛배부름, 변비, 과민성 설사, 대장암

비뇨생식기 질환

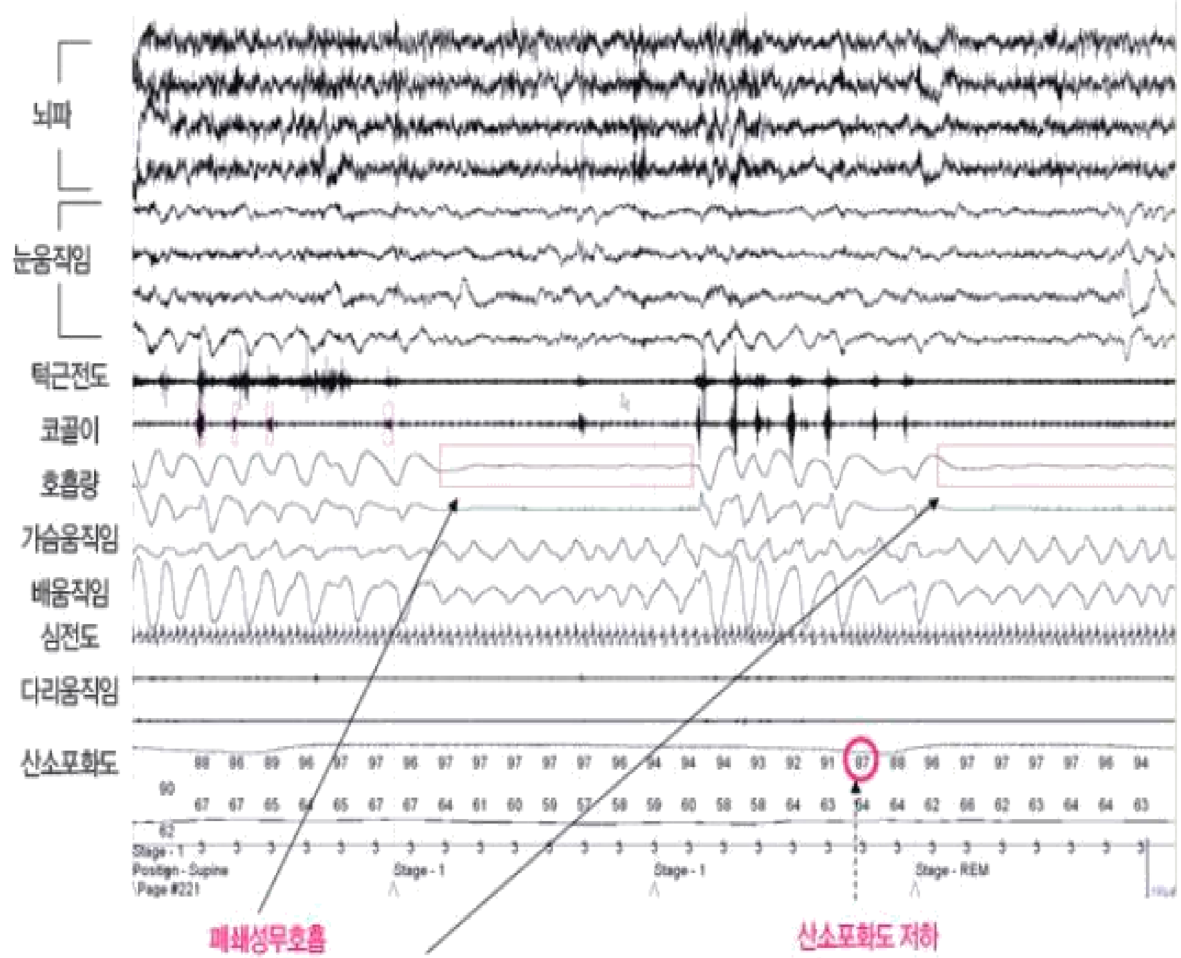
성욕/성기능 저하, 생리통, 자연유산, 저체중아, 조산, 유방암

Typical Brain Waves with respect to Sleep Stages

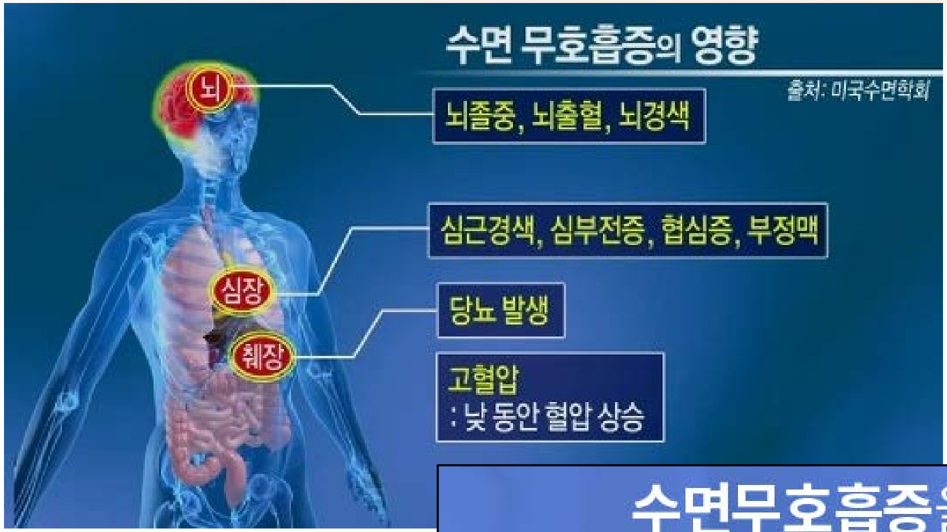


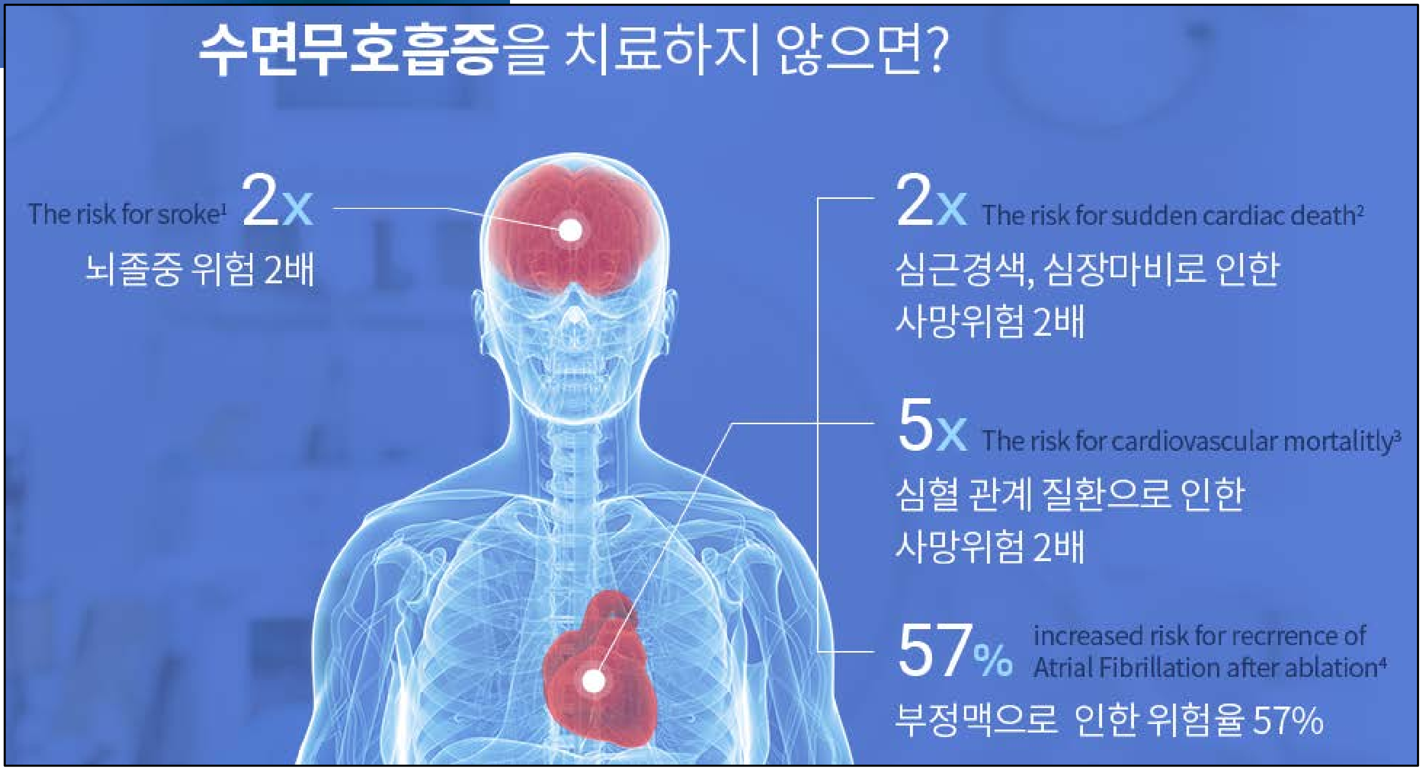


수면무호흡증환자의 수면다원검사 결과



How serious is Sleep Apnea?



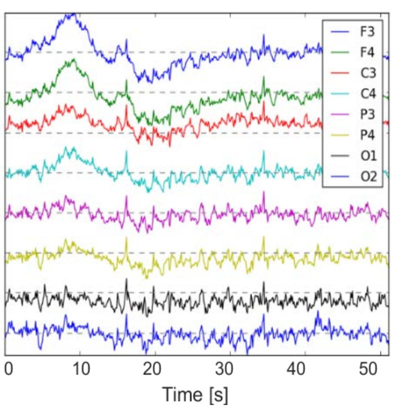


Automated Sleep Stage Scoring & Apnea Monitoring

Automated Sleep Stage Scoring via PSG Data Deep Learning

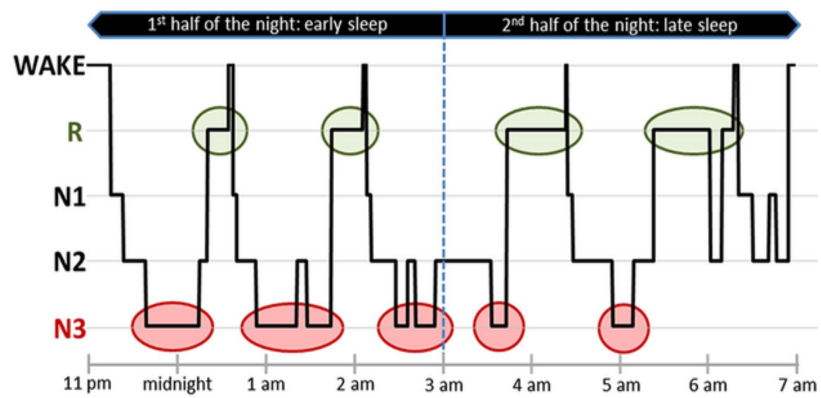
- End-to-end deep learning architecture w/o transformation or signal processing
- Learn to representative features from PSG data (EEG, EOG, ECG, EMG, etc.)
- Learn to temporal context of the features in intra epoch as well as inter epochs

< INPUT = PSG Dataset >



< Deep Learning :: IITNet >

< OUTPUT = Sleep Hypnogram :: Sleep Stage Scoring >



PSG Datasets

1) **<u>Sleep EDF</u>** (European Data Format) Expanded :: PSG (EEG 4 channels: Fpz-Cz, Pz-Oz)

   - MCH-Westeinde Hospital, Netherlands

   - 정상인 (39 건), 수면제(Temazepam) 복용자 (22 건), 수면 단계 분류 포함

2) **<u>SLEEP BRL</u>** (BioRadioLocation) :: PSG (EEG 16 channels) & Bio-radar (3.6 – 4.0 GHz, CW)

   - Almazov National Medical Research Centre, Russia

   - 정상인 (28 건), 불면증 (4건), 수면 단계 분류 포함

3) **<u>MASS</u>** (Montreal Archive of Sleep Studies)

   :: PSG (EEG 4 or 16 channels, EOG, EMG, ECG, 호흡)

   - Center for Advanced Research in Sleep Medicine, Canada

   - 정상인 및 수면무호흡 환자 (200건), 수면 단계 분류(Wake, RAM, S1, S2, S3) 포함

4) **<u>SHHS</u>** (Sleep Heart Health Study) :: PSG (EEG 4 channels)

   - National Heart Lung & Blood Institute, USA

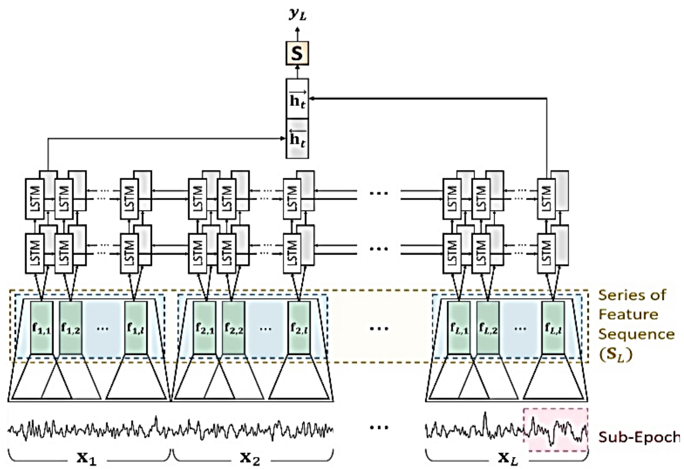
   - 정상인 (6,441 건), 수면 단계 분류 (Wake, RAM, S1, S2, S3) 포함

Sleep Stage Classification based on Brain Waves

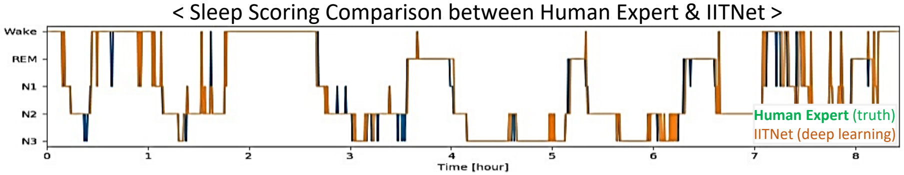
Intra- & Inter-epoch Temporal Context

- ✓ Sleep-related Features were extracted by CNN
- ✓ Temporal Context of Features was analyzed by RNN

< Intra- & Inter-Epoch Temporal Context Network :: IITNet >



< Sleep Scoring Comparison between Human Expert & IITNet >

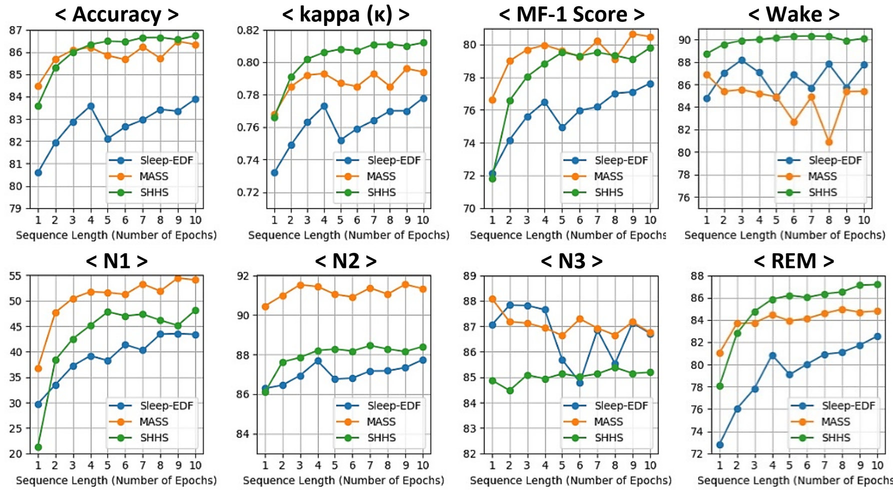


< Confusion Matrix of IITNet for Three Datasets >

L	Truth	Sleep EDF Prediction W	N1	N2	N3	REM	MASS Prediction W	N1	N2	N3	REM	SHHS Prediction W	N1	N2	N3	REM
1	W	7,171 (87%)	455 (5%)	246 (3%)	24 (0%)	389 (5%)	4,917 (87%)	391 (7%)	130 (2%)	12 (0%)	222 (4%)	339,276 (90%)	2,997 (1%)	22,149 (6%)	1,122 (0%)	10,590 (3%)
	N1	470 (17%)	661 (24%)	655 (23%)	4 (0%)	1,014 (36%)	437 (10%)	1,378 (30%)	1,297 (29%)	0 (0%)	1,412 (31%)	14,005 (21%)	9,161 (14%)	25,053 (38%)	45 (0%)	17,683 (27%)
	N2	434 (2%)	171 (1%)	15,539 (87%)	667 (4%)	988 (6%)	143 (0%)	550 (2%)	26,676 (91%)	814 (3%)	1,029 (4%)	21,260 (3%)	5,114 (1%)	628,432 (87%)	32,044 (4%)	31,791 (4%)
	N3	125 (2%)	4 (0%)	636 (11%)	4,935 (87%)	3 (0%)	11 (0%)	0 (0%)	949 (13%)	6,607 (87%)	0 (0%)	1,245 (1%)	3 (0%)	32,191 (15%)	188,318 (85%)	224 (0%)
	REM	438 (6%)	346 (4%)	1,140 (15%)	4 (0%)	5,789 (75%)	137 (1%)	653 (6%)	719 (7%)	1 (0%)	8,910 (86%)	12,961 (5%)	2,918 (1%)	33,331 (14%)	227 (0%)	195,393 (80%)

Results & Discoveries

- ✓ Signals of Multiple Epochs were used as an Input



< Performance Comparison >

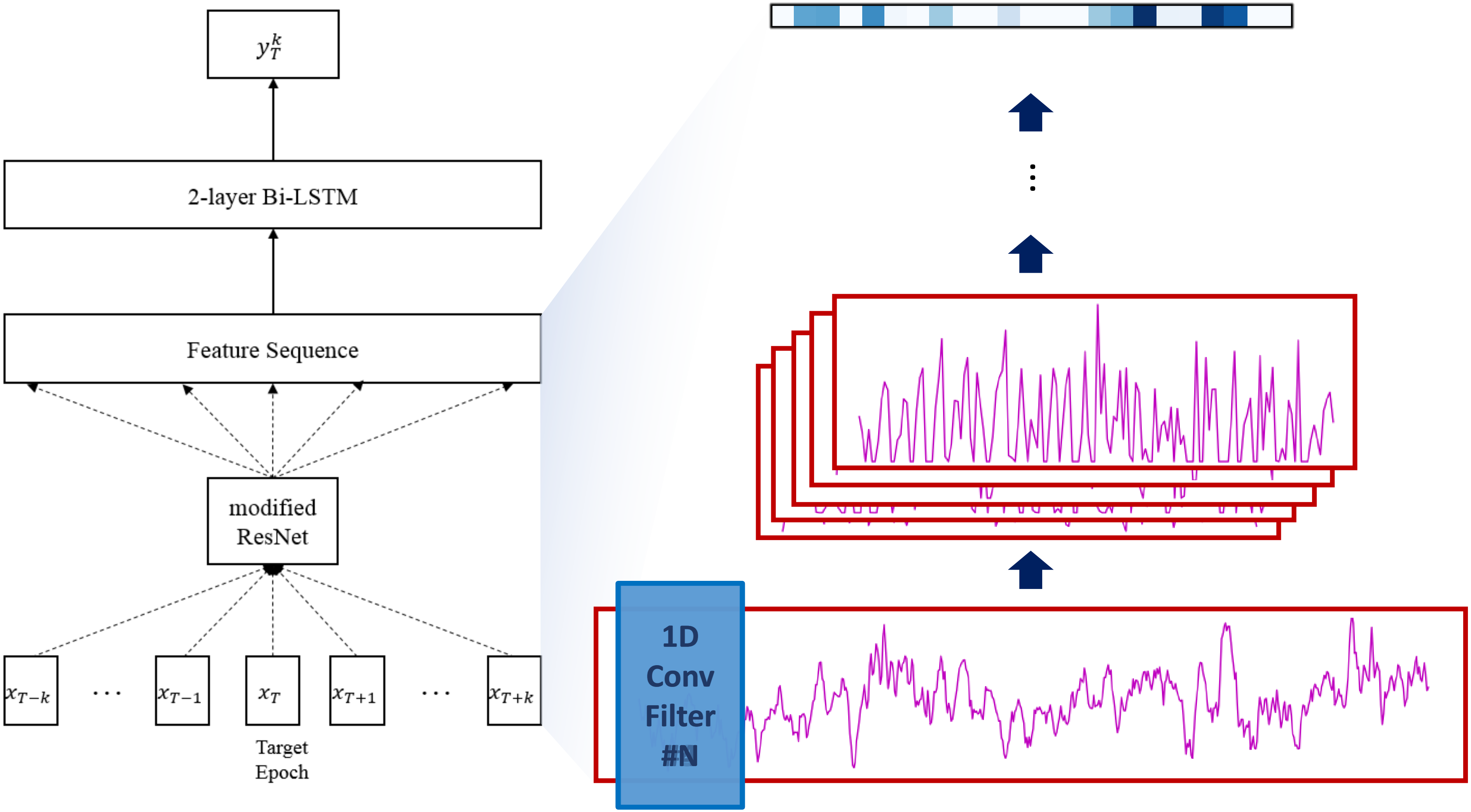
DB	Article	Method: Architecture	Input Channel	Subjects	Approach	Input Type	Sequence Length	Overall Metrics: ACC	MF1	k
Sleep-EDF	IITNet	CNN + RNN	Fpz-Cz	20	Many-to-one	Raw signal	10 (9 past)	83.9	77.6	0.78
		CNN + RNN	Fpz-Cz	20	Many-to-one	Raw signal	4 (3 past)	83.6	76.5	0.77
		CNN + RNN	Fpz-Cz	20	One-to-one	Raw signal	1	80.6	72.1	0.73
	Supratak	CNN + RNN	Fpz-Cz	20	Many-to-one	Raw signal	Whole night epochs	82.0	76.9	0.76
	Phan	Multitask 1-max CNN	Fpz-Cz	20	One-to-many	Time-frequency spectrogram	1	81.9	73.8	0.74
	Vilamala	CNN	Fpz-Cz	20	Many-to-one	Time-frequency spectrogram	5 (2 past and futrue)	81.3	76.5	0.74
	Tsinalis	CNN	Fpz-Cz	20	Many-to-one	Raw signal	5 (2 past and future)	74.8	69.8	0.65
MASS	IITNet	CNN + RNN	F4-EOG (left)	62	Many-to-one	Raw signal	10 (9 past)	86.3	80.5	0.79
		CNN + RNN	F4-EOG (left)	62	Many-to-one	Raw signal	4 (3 past)	86.2	80.0	0.79
		CNN + RNN	F4-EOG (left)	62	One-to-one	Raw signal	1	84.5	76.6	0.77
	Supratak	CNN + RNN	F4-EOG (left)	62	Many-to-one	Raw signal	Whole night epochs	86.2	81.7	0.80
	Dong	MNN + RNN	F4-EOG (left)	62	Many-to-one	Handcrafted features	5 (4 past)	85.9	80.5	0.79
	Phan	Multitask 1-max CNN	C4-A1	200	One-to-many	Time-frequency spectrogram	1	78.6	70.6	0.70
SHHS	IITNet	CNN + RNN	C4-A1	5728	Many-to-one	Raw signal	10 (9 past)	86.7	79.8	0.81
		CNN + RNN	C4-A1	5728	Many-to-one	Raw signal	4 (3 past)	86.3	78.8	0.81
		CNN + RNN	C4-A1	5728	One-to-one	Raw signal	1	83.6	71.8	0.77
	Sors	CNN	C4-A1	5728	Many-to-one	Raw signal	4 (2 past and 1 future)	86.8	78.5	0.81

arXiv preprint arXiv:1902.06562 (2019)

https://arxiv.org/abs/1902.06562

Proposed Deep Learning Model :: IITNet

- **Intra- and Inter-epoch Temporal Context Network (IITNet)**



H. Seo, S. Back, S. Lee, D. Park, T. Kim, K. Lee*, "Intra- and Inter-epoch Temporal Context Network (IITNet) for Automatic Sleep Scoring on Raw Single-channel EEG," *Biomedical Signal Processing and Control*, IF: 2.943 Revising after Review

Proposed Deep Learning Model :: IITNet

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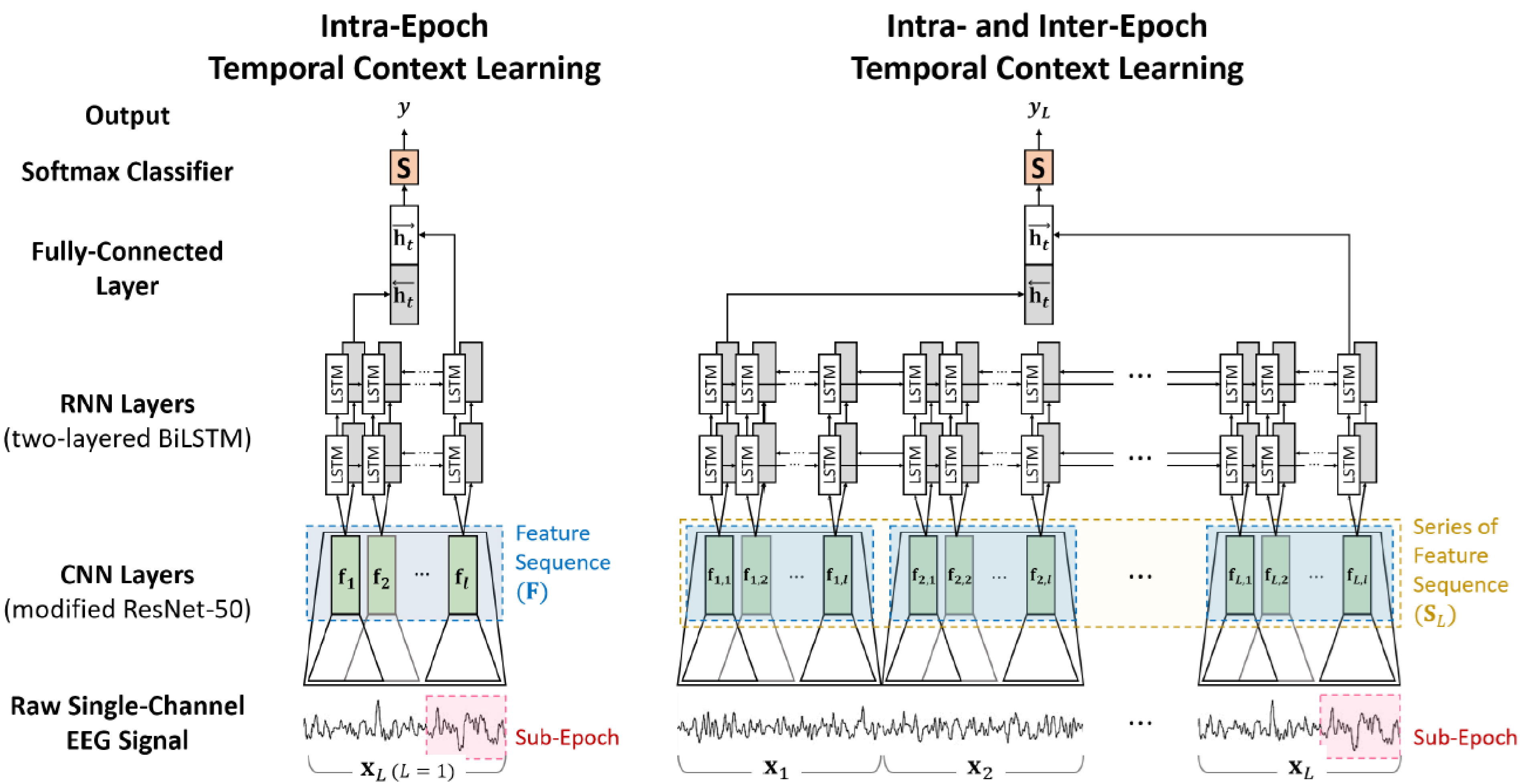
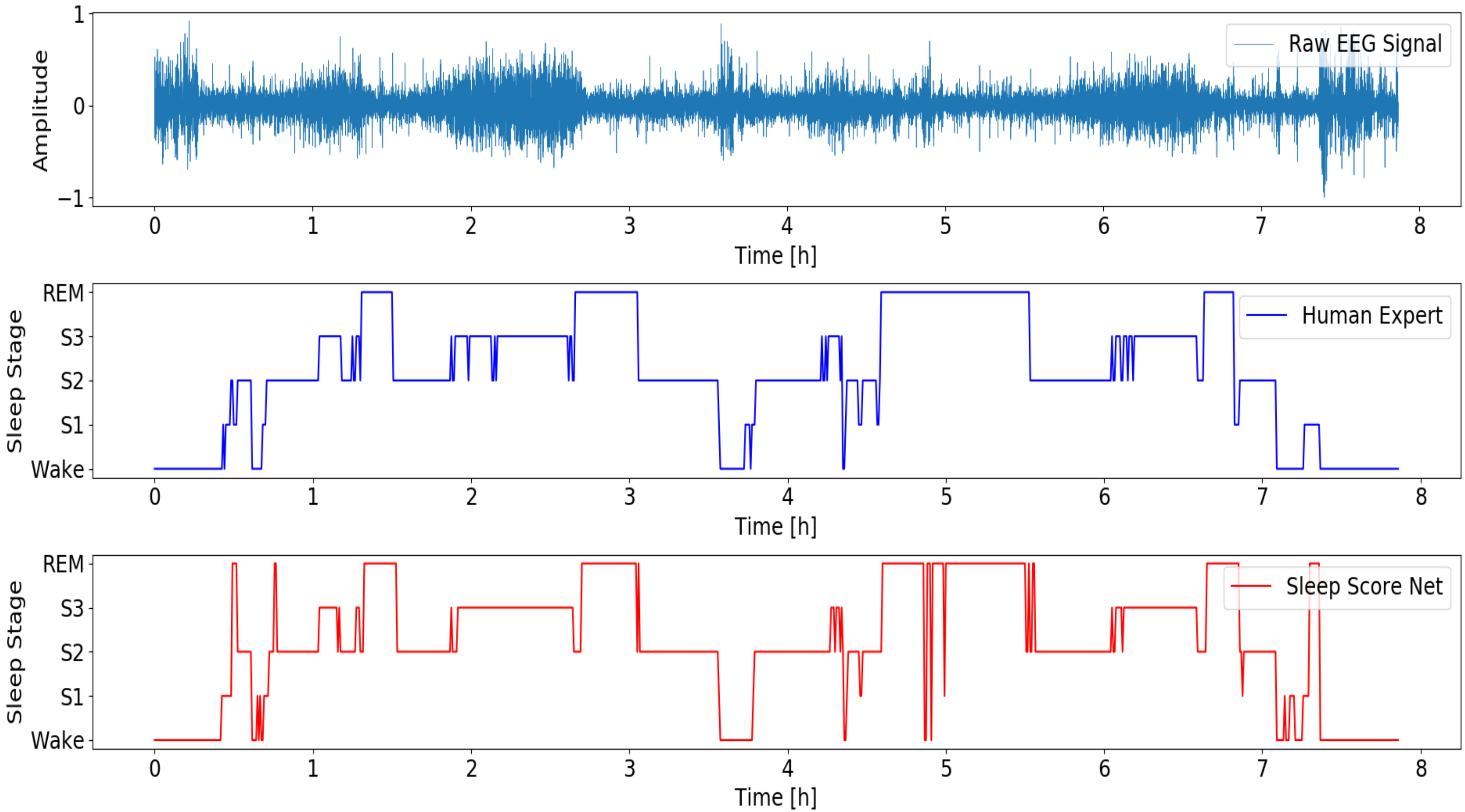


H. Seo, S. Back, S. Lee, D. Park, T. Kim, K. Lee*, "Intra- and Inter-epoch Temporal Context Network (IITNet) for Automatic Sleep Scoring on Raw Single-channel EEG," *Biomedical Signal Processing and Control*, IF: 2.943 Revising after Review

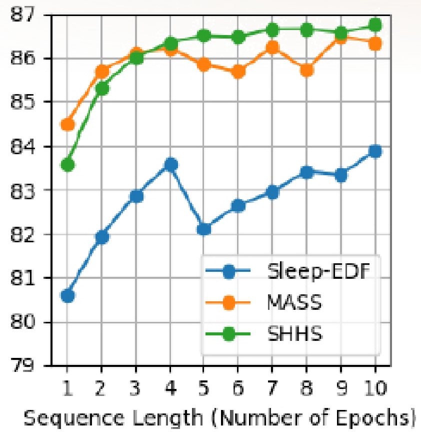
Sleep Stage Classification based on Brain Waves

- **Intra- and Inter-epoch Temporal Context Network (IITNet)**

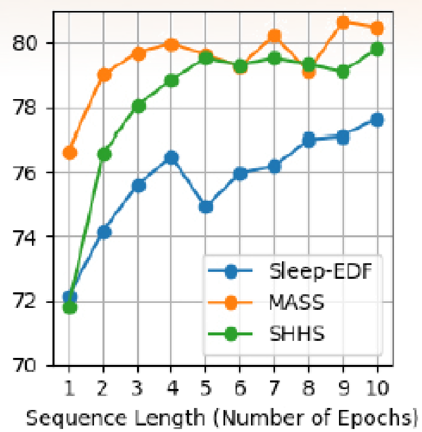


H. Seo, S. Back, S. Lee, D. Park, T. Kim, K. Lee*, "Intra- and Inter-epoch Temporal Context Network (IITNet) for Automatic Sleep Scoring on Raw Single-channel EEG," *Biomedical Signal Processing and Control*, IF: 2.943 Revising after Review

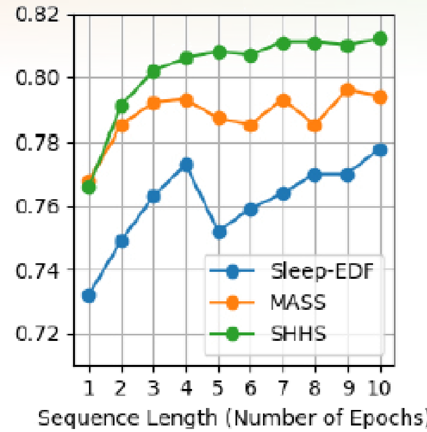
Performance of IITNet with the Sequence Length (L)



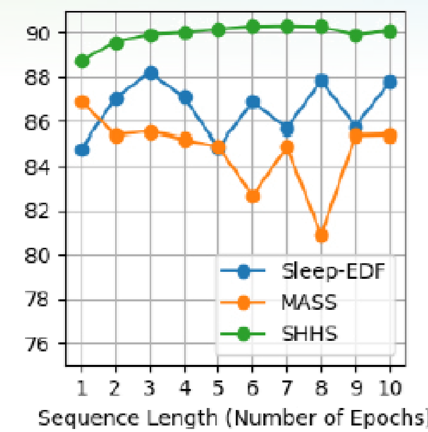
(a) Overall Accuracy [%]



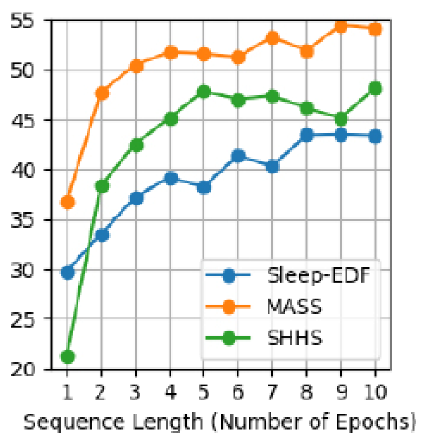
(b) Macro-F1 [%]



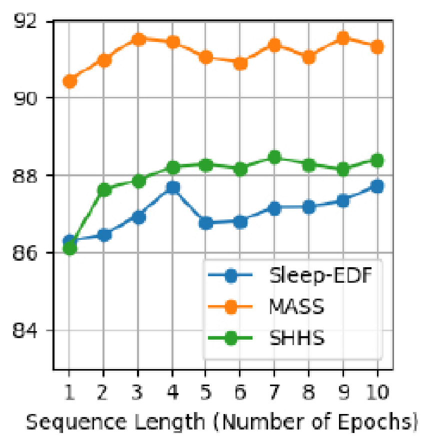
(c) Cohen's Kappa (κ)



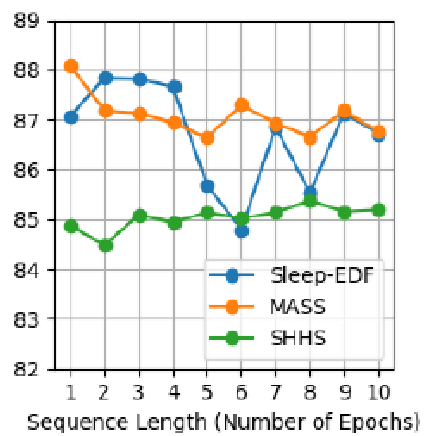
(d) F1 of W [%]



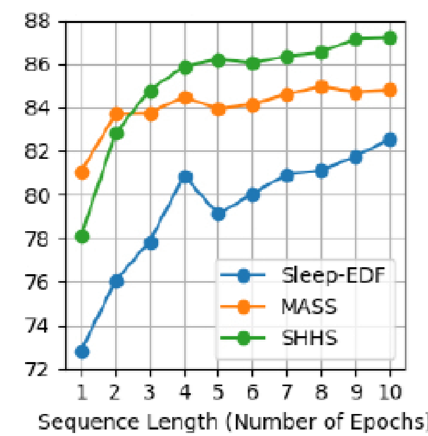
(e) F1 of N1 [%]



(f) F1 of N2 [%]



(g) F1 of N3 [%]



(h) F1 of REM [%]

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Confusion matrix of IITNet with the Sequence Length (L)

L	Truth	Sleep EDF Prediction					MASS Prediction					SHHS Prediction				
		W	N1	N2	N3	REM	W	N1	N2	N3	REM	W	N1	N2	N3	REM
1	W	7,171 (87%)	455 (5%)	246 (3%)	24 (0%)	389 (5%)	4,917 (87%)	391 (7%)	130 (2%)	12 (0%)	222 (4%)	339,276 (90%)	2,997 (1%)	22,149 (6%)	1,122 (0%)	10,590 (3%)
	N1	470 (17%)	661 (24%)	655 (23%)	4 (0%)	1,014 (36%)	437 (10%)	1,378 (30%)	1,297 (29%)	0 (0%)	1,412 (31%)	14,005 (21%)	9,161 (14%)	25,053 (38%)	45 (0%)	17,683 (27%)
	N2	434 (2%)	171 (1%)	15,539 (87%)	667 (4%)	988 (6%)	143 (0%)	550 (2%)	26,676 (91%)	814 (3%)	1,029 (4%)	21,260 (3%)	5,114 (1%)	628,432 (87%)	32,044 (4%)	31,791 (4%)
	N3	125 (2%)	4 (0%)	636 (11%)	4,935 (87%)	3 (0%)	11 (0%)	0 (0%)	949 (13%)	6,607 (87%)	0 (0%)	1,245 (1%)	3 (0%)	32,191 (15%)	188,318 (85%)	224 (0%)
	REM	438 (6%)	346 (4%)	1,140 (15%)	4 (0%)	5,789 (75%)	137 (1%)	653 (6%)	719 (7%)	1 (0%)	8,910 (86%)	12,961 (5%)	2,918 (1%)	33,331 (14%)	227 (0%)	195,393 (80%)
4	W	7,213 (88%)	494 (6%)	261 (3%)	40 (0%)	160 (2%)	4,677 (85%)	464 (8%)	154 (3%)	14 (0%)	185 (3%)	339,709 (91%)	6,870 (2%)	17,188 (5%)	1,449 (0%)	6,155 (2%)
	N1	547 (20%)	936 (33%)	673 (24%)	21 (1%)	627 (22%)	448 (10%)	2,051 (45%)	936 (21%)	1 (0%)	1,083 (24%)	14,148 (21%)	25,264 (38%)	18,095 (27%)	32 (0%)	8,364 (13%)
	N2	389 (2%)	219 (1%)	15,864 (89%)	712 (4%)	615 (3%)	164 (1%)	460 (2%)	27,096 (93%)	814 (3%)	675 (2%)	19,969 (3%)	9,295 (1%)	635,332 (88%)	32,273 (4%)	21,495 (3%)
	N3	49 (1%)	0 (0%)	592 (10%)	5,058 (89%)	4 (0%)	5 (0%)	0 (0%)	1,106 (15%)	6,456 (85%)	0 (0%)	1,304 (1%)	2 (0%)	31,467 (14%)	188,900 (85%)	192 (0%)
	REM	203 (3%)	321 (4%)	995 (13%)	7 (0%)	6,191 (80%)	191 (2%)	426 (4%)	764 (7%)	0 (0%)	9,039 (87%)	8,511 (3%)	4,500 (2%)	20,123 (8%)	266 (0%)	211,416 (86%)
10	W	6,982 (88%)	506 (6%)	261 (3%)	32 (0%)	153 (2%)	4,375 (84%)	405 (8%)	194 (4%)	15 (0%)	199 (4%)	332,831 (92%)	7,084 (2%)	15,947 (4%)	1,289 (0%)	4,776 (1%)
	N1	513 (18%)	1,133 (40%)	635 (23%)	24 (1%)	499 (18%)	432 (10%)	2,187 (49%)	942 (21%)	3 (0%)	907 (20%)	14,470 (22%)	27,721 (42%)	17,201 (26%)	21 (0%)	6,426 (10%)
	N2	264 (1%)	390 (2%)	15,741 (88%)	799 (4%)	605 (3%)	125 (0%)	479 (2%)	27,063 (93%)	871 (3%)	653 (2%)	20,742 (3%)	10,551 (1%)	634,832 (88%)	31,589 (4%)	20,010 (3%)
	N3	95 (2%)	7 (0%)	562 (10%)	5,029 (88%)	10 (0%)	6 (0%)	0 (0%)	1,081 (14%)	6,479 (86%)	1 (0%)	1,152 (1%)	2 (0%)	31,130 (14%)	189,108 (85%)	228 (0%)
	REM	128 (2%)	379 (5%)	884 (11%)	12 (0%)	6,314 (82%)	121 (1%)	539 (5%)	793 (8%)	1 (0%)	8,966 (86%)	7,731 (3%)	3,959 (2%)	19,312 (8%)	331 (0%)	213,448 (87%)

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Performance of IITNet compared to Others with SleepEDF

Method								Overall Metrics			Per-class F1 Score				
Dataset	Model	Architecture	Channel	Input	Approach	Sequence Length	Subjects	Acc.	MF1	κ	W	N1	N2	N3	REM
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	One-to-One	1	20	80.6	72.1	0.73	84.7	29.8	86.3	87.1	72.8
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	2 (1 past)	20	81.9	74.2	0.75	87.0	33.5	86.5	87.8	76.0
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	3 (2 past)	20	82.9	75.6	0.76	88.2	37.2	86.9	87.8	77.8
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	4 (3 past)	20	**83.6**	**76.5**	**0.77**	87.1	39.2	87.7	87.7	80.9
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	5 (4 past)	20	82.1	74.9	0.75	84.8	38.3	86.8	85.7	79.1
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	6 (5 past)	20	82.6	76.0	0.76	86.9	41.4	86.8	84.8	80.0
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	7 (6 past)	20	83.0	76.2	0.76	85.7	40.3	87.2	86.9	80.9
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	8 (7 past)	20	83.4	77.0	0.77	87.8	43.5	87.2	85.5	81.1
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	9 (8 past)	20	83.3	77.1	0.77	85.8	43.6	87.3	87.1	81.7
SleepEDF	**IITNet**	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	10 (9 past)	20	<u>83.9</u>	<u>77.6</u>	<u>0.78</u>	87.7	43.4	87.7	86.7	82.5
SleepEDF	Supratak [21]	CNN + RNN	Fpz-Cz	Raw Signal	Many-to-One	Whole night epochs	20	82.0	76.9	0.76	84.7	46.6	89.8	84.8	82.4
SleepEDF	Phan [32]	Multitask 1-max CNN	Fpz-Cz	Spectrogram	One-to-Many	1	20	81.9	73.8	0.74	-	-	-	-	-
SleepEDF	Vilamala [24]	CNN	Fpz-Cz	Spectrogram	Many-to-One	5 (2 past, future)	20	81.3	76.5	0.74	80.9	47.4	86.2	86.2	81.9
SleepEDF	Tsinalis [25]	CNN	Fpz-Cz	Raw Signal	Many-to-One	5 (2 past, future)	20	74.8	69.8	0.65	43.7	80.6	84.9	74.5	65.4

<u>H. Seo</u>, S. Back, S. Lee, D. Park, T. Kim, K. Lee*, "Intra- and Inter-epoch Temporal Context Network (IITNet) for Automatic Sleep Scoring on Raw Single-channel EEG," *Biomedical Signal Processing and Control*, IF: 2.943 Revising after Review

Performance of IITNet compared to Others with MASS

Method								Overall Metrics			Per-class F1 Score				
Dataset	Model	Architecture	Channel	Input	Approach	Sequence Length	Subjects	Acc.	MF1	κ	W	N1	N2	N3	REM
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	One-to-One	1	62	84.5	76.6	0.77	86.9	36.8	90.5	88.1	81.0
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	2 (1 past)	62	85.7	79.0	0.79	85.4	47.7	91.0	87.2	83.7
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	3 (2 past)	62	86.1	79.7	0.79	85.5	50.5	91.5	87.1	83.7
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	4 (3 past)	62	**86.2**	**80.0**	**0.79**	85.2	51.8	91.4	86.9	84.5
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	5 (4 past)	62	85.8	79.6	0.79	84.9	51.6	91.0	86.6	83.9
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	6 (5 past)	62	85.7	79.3	0.79	82.7	51.3	90.9	87.3	84.1
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	7 (6 past)	62	86.2	80.2	0.79	84.9	53.3	91.4	86.9	84.6
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	8 (7 past)	62	85.7	79.1	0.79	80.9	51.9	91.1	86.7	85.0
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	9 (8 past)	62	<u>86.5</u>	80.7	<u>0.80</u>	85.4	54.5	91.5	87.2	84.7
MASS	**IITNet**	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	10 (9 past)	62	86.3	80.5	0.79	85.4	54.1	91.3	86.8	84.8
MASS	Supratak [21]	CNN + RNN	F4-EOG (left)	Raw Signal	Many-to-One	Whole night epochs	62	86.2	<u>81.7</u>	0.80	87.3	59.8	90.3	81.5	89.3
MASS	Dong [33]	Mixed RNN	F4-EOG (left)	Handcrafted Features	Many-to-One	5 (4 past)	62	85.9	80.5	0.79	84.6	56.3	90.7	84.8	86.1
MASS	Phan [32]	Multitask 1-max CNN	C4-A1	Spectrogram	One-to-Many	1	200	78.6	70.6	0.70	-	-	-	-	-

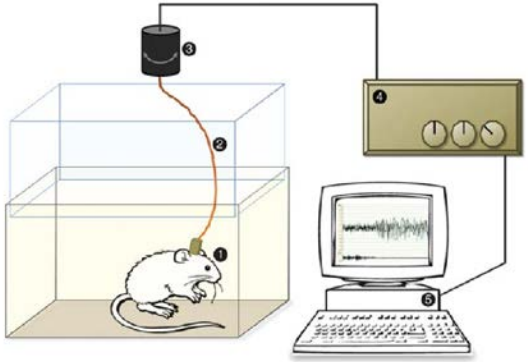
<u>H. Seo</u>, S. Back, S. Lee, D. Park, T. Kim, K. Lee*, "Intra- and Inter-epoch Temporal Context Network (IITNet) for Automatic Sleep Scoring on Raw Single-channel EEG," *Biomedical Signal Processing and Control*, IF: 2.943 Revising after Review

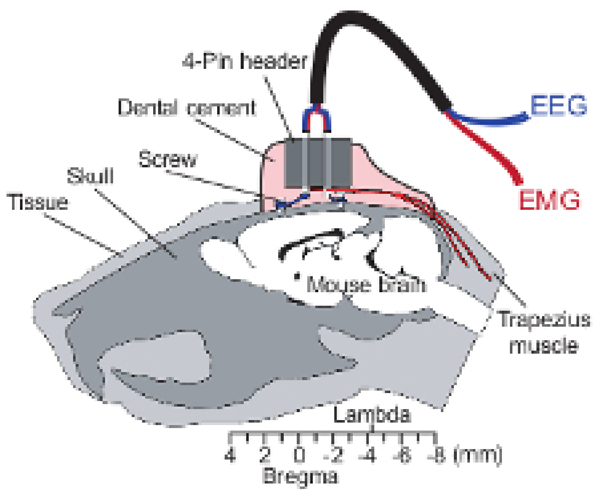
Performance of IITNet compared to Others with SHHS

Method								Overall Metrics			Per-class F1 Score				
Dataset	Model	Architecture	Channel	Input	Approach	Sequence Length	Subjects	Acc.	MF1	κ	W	N1	N2	N3	REM
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	One-to-One	1	5,791	83.6	71.8	0.77	88.7	21.3	86.1	84.9	78.1
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	2 (1 past)	5,791	85.3	76.6	0.79	89.6	38.4	87.6	84.5	82.8
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	3 (2 past)	5,791	86.0	78.0	0.80	89.9	42.5	87.9	85.1	84.8
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	4 (3 past)	5,791	**86.3**	**78.8**	**0.81**	90.0	45.2	88.2	84.9	85.9
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	5 (4 past)	5,791	86.5	79.5	0.81	90.2	47.8	88.3	85.1	86.2
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	6 (5 past)	5,791	86.5	79.3	0.81	90.3	47.0	88.2	85.0	86.0
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	7 (6 past)	5,791	86.6	79.5	0.81	90.3	47.4	88.5	85.1	86.3
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	8 (7 past)	5,791	86.7	79.3	0.81	90.3	46.2	88.3	85.4	86.5
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	9 (8 past)	5,791	86.6	79.1	0.81	89.9	45.2	88.2	85.2	87.1
SHHS	**IITNet**	CNN + RNN	C4-A1	Raw Signal	Many-to-One	10 (9 past)	5,791	86.7	79.8	0.81	90.1	48.1	88.4	85.2	87.2
SHHS	Sors [22]	CNN	C4-A1	Raw Signal	Many-to-One	4 (2 past, 1 future)	5,728	86.8	78.5	0.81	91.4	42.7	88.0	84.9	85.4

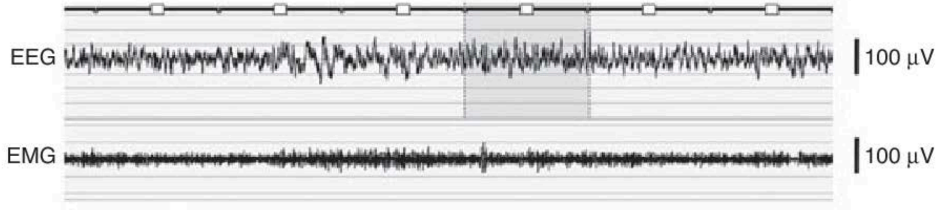
H. Seo, S. Back, S. Lee, D. Park, T. Kim, K. Lee*, "Intra- and Inter-epoch Temporal Context Network (IITNet) for Automatic Sleep Scoring on Raw Single-channel EEG," *Biomedical Signal Processing and Control*, IF: 2.943 Revising after Review

IITNet applied to Mice Sleep Scoring

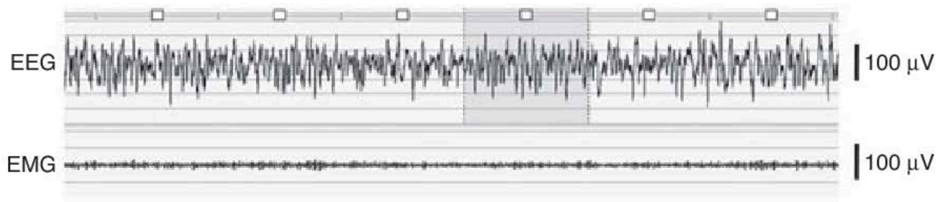




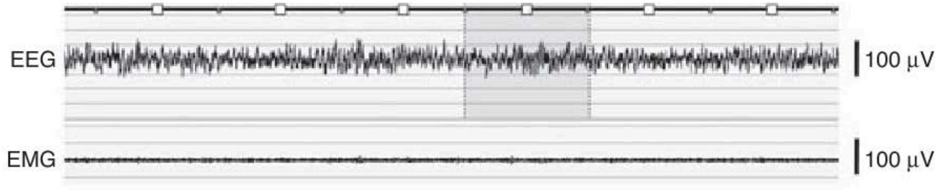
Wakefulness (mixed frequencies, muscle tone)



Non REM Sleep (high magnitude of 1~4 Hz, muscle tone)



REM Sleep (theta waves of 6~9 Hz, EMG is flat)



동물 뇌파에 대한 IITNet의 최적화

- Batch Size: 90 epochs
- Sampling Rate: 25 ~ 2000 Hz, Window Time: 0.025 ~ 0.25 s, Overlapping Rate: 0 ~ 90%

=> Best @ Window Time: 0.025 s, Overlapping Rate: 70%

Sampling Rate [Hz]	25	50	100	125	200	250	400	500	1000	2000
Accuracy	87.6%	92.0%	92.8%	93.8%	96.0%	95.8%	96.1%	95.6%	95.5%	93.8%

Sampling Rate [Hz] 400	**Input Length** 10	20	30	40	50	60	70	80	90	100
Overlapping Rate	**Window Time [s]** 0.0250	0.0500	0.0750	0.1000	0.1250	0.1500	0.1750	0.2000	0.2250	0.2500
0%	95.9%	95.6%	95.3%	95.3%	95.3%	95.1%	94.9%	94.8%	94.4%	94.3%
10%	96.0%	95.6%	95.6%	95.5%	95.2%	95.1%	95.0%	94.7%	94.8%	94.6%
20%	96.0%	95.9%	95.6%	95.4%	95.3%	95.3%	95.2%	95.1%	94.7%	94.8%
30%	96.1%	95.9%	95.7%	95.5%	95.6%	95.3%	95.2%	95.3%	95.1%	94.8%
40%	96.4%	96.1%	96.0%	95.7%	95.5%	95.5%	95.4%	95.3%	95.3%	95.0%
50%	96.1%	96.0%	95.8%	95.8%	95.7%	95.7%	95.4%	95.5%	95.3%	95.3%
60%	96.4%	96.2%	96.0%	95.8%	96.0%	95.6%	95.6%	95.7%	95.4%	95.4%
70%	96.5%	96.4%	96.2%	96.0%	95.9%	95.8%	95.8%	95.7%	95.7%	95.6%
80%	96.3%	96.4%	96.3%	96.2%	96.2%	96.1%	96.0%	95.8%	95.8%	95.9%
90%	96.1%	96.3%	96.4%	96.1%	96.3%	96.2%	96.2%	96.2%	95.9%	96.1%

동물 뇌파에 대한 IITNet의 최적화

- Batch Size: 90 epochs,

  Sampling Rate: 400 Hz, Window Time: 0.025 s, Overlapping Rate: 90%

Channel	Normalization	
	X	O
EEG1	95.9%	96.5%
EEG2	96.1%	96.3%
EMG	81.2%	82.2%

Vertical Resolution	Normalization	
	X	O
Float 16bit	96.1%	96.2%
Float 32bit	96.1%	96.4%
Float 64bit	95.9%	96.3%

(Overlapping Rate: 90%)

Channel	Accuracy	Correct	Count	M00	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20	M21	M22	M23
EEG1	**96.1%**	**199,364**	**207,360**	**94%**	**94%**	**94%**	**96%**	**95%**	**97%**	**97%**	**97%**	**97%**	**96%**	**95%**	**90%**	**97%**	**98%**	**98%**	**97%**	**96%**	**96%**	**95%**	**95%**	**97%**	**98%**	**98%**	**98%**
Wake	96.7%	90,327	93,439	95%	94%	87%	97%	93%	97%	99%	98%	99%	###	99%	99%	96%	99%	99%	97%	94%	98%	93%	93%	98%	98%	99%	98%
NREM	96.9%	97,844	101,013	95%	95%	98%	99%	98%	98%	97%	97%	96%	95%	93%	83%	99%	98%	98%	97%	99%	96%	99%	98%	98%	99%	97%	99%
REM	86.7%	11,193	12,908	87%	87%	89%	77%	93%	92%	94%	92%	90%	83%	74%	65%	84%	92%	96%	94%	84%	85%	88%	90%	90%	92%	89%	81%
EEG2	**96.2%**	**199,473**	**207,360**	**94%**	**93%**	**94%**	**96%**	**95%**	**97%**	**97%**	**97%**	**98%**	**97%**	**97%**	**94%**	**97%**	**98%**	**98%**	**97%**	**98%**	**93%**	**97%**	**97%**	**96%**	**96%**	**97%**	**98%**
Wake	96.7%	90,390	93,439	94%	93%	95%	94%	92%	96%	97%	96%	99%	99%	98%	98%	96%	99%	99%	97%	97%	###	97%	98%	99%	93%	97%	97%
NREM	96.4%	97,347	101,013	94%	93%	95%	###	99%	97%	98%	###	98%	97%	96%	91%	99%	97%	97%	96%	98%	90%	97%	97%	94%	99%	97%	99%
REM	90.9%	11,736	12,908	88%	96%	90%	81%	98%	97%	90%	86%	89%	82%	92%	85%	88%	93%	98%	99%	95%	88%	93%	85%	83%	96%	98%	94%
EMG	**81.5%**	**169,025**	**207,360**	**92%**	**90%**	**92%**	**95%**	**83%**	**66%**	**93%**	**92%**	**71%**	**95%**	**91%**	**91%**	**64%**	**69%**	**72%**	**88%**	**71%**	**78%**	**81%**	**85%**	**81%**	**70%**	**75%**	**73%**
Wake	82.2%	76,847	93,439	94%	97%	86%	94%	98%	76%	98%	96%	74%	99%	85%	88%	32%	72%	54%	98%	65%	63%	77%	95%	77%	98%	87%	54%
NREM	87.7%	88,572	101,013	91%	85%	96%	98%	71%	61%	95%	99%	78%	97%	99%	99%	98%	75%	97%	89%	82%	95%	97%	86%	97%	50%	74%	99%
REM	27.9%	3,606	12,908	83%	91%	94%	86%	40%	0%	42%	0%	2%	59%	75%	58%	0%	0%	0%	8%	21%	0%	0%	0%	0%	35%	0%	0%

Contents

AI-based Structural Health Monitoring for Active Safety

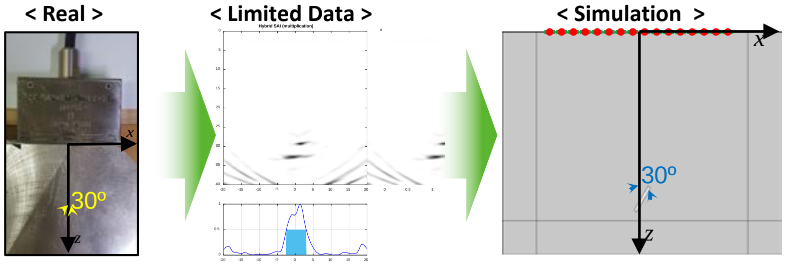
High Reliability of Structural Safety

- **NDE Assistant & Adaptive Solution based on AI**
  - ✓ Higher Probability of Detection
  - ✓ Faster In-Service Inspection
  - ✓ Novel Insight & Technique for SHM with AR / VR
  - → Improved Technical Independence in Maintenance

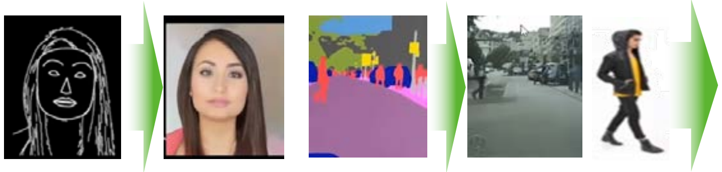
➢ **Safe, Safe, and Safe Korean Nuclear Power Plants**

Innovation & Convergence for AI NDE

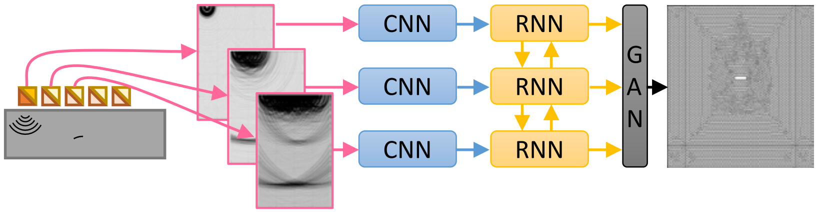
- **Digital Twin for NDE** based on DNN & FEM



- **Super Reconstruction** based on AE & GAN
  - Resolution: Coarse → Fine
  - Dimension Reconstruction: 1D → 2D → 3D



- **Dynamic Context NDE** based on CRNN & GAN
  : Single Shot → Continuous Moving

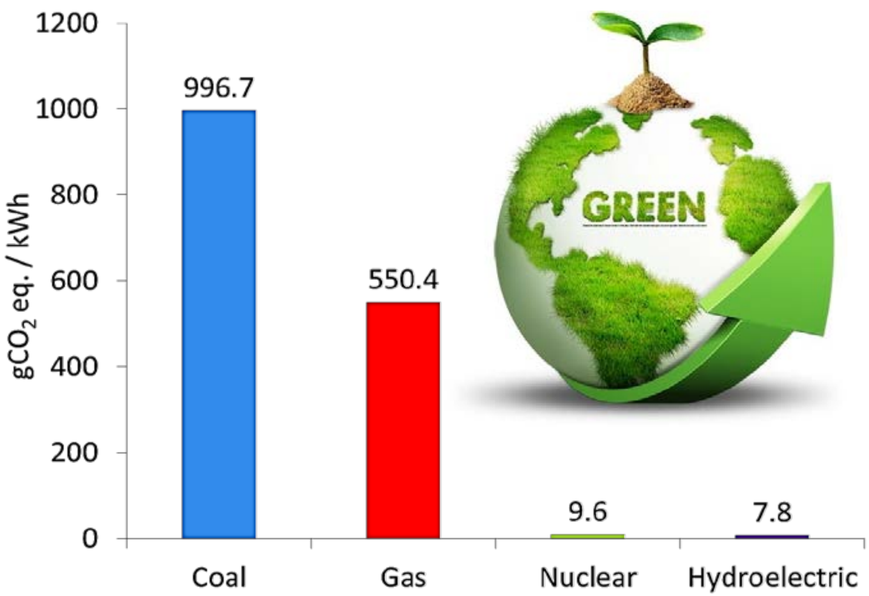


AI-based Structural Health Monitoring for Active Safety

Ecofriendly & Sustainable Atomic Energy

- **NDE for Radioactive Waste Containers is Crucial**
  - ✓ Early-Stage Internal Corrosion
  - ✓ Prevention of Radiation Leak
  - → Thorough Following-up Management

➢ **All about Atomic Energy must be Green & Safe from Beginning to End**



Beyond Structural Health Care

- **Advanced NDE Technology plays a Key Role in Safe, Ecofriendly, and Sustainable Atom Energy**
  - → Spin-off Effect in Industrial and Medical Fields
  - → Well-Being of Humanity

➢ **The More People believe NDE Safety, The More Atom Energy is Loved**

Collaboration with AI-based IoT & Smart Health Care

▪ 비접촉 실시간 호흡 상태 및 수면 단계 인공지능 분석을 통한 스마트 케어 시스템

< Noncontact Biosensing >

< Pen tilt moving UWB sensor >

< Personal robot incl. UWB >

< Pet robot incl. UWB >

Smart Pet
- 유아 관찰
- 노인 관찰

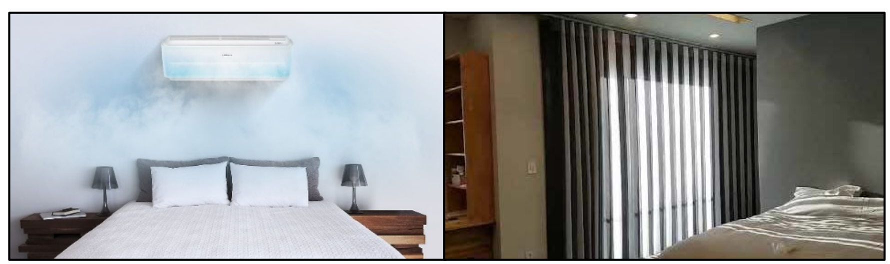
Smart Bed
- 수면 장애 방지
- 수면 및 기상 유도

Smart Hospital Bed
- 환자 이동 파악
- 환자 상태 관찰

Smart Cradle
- 영아 질식사 방지
- 응급 상황 알림

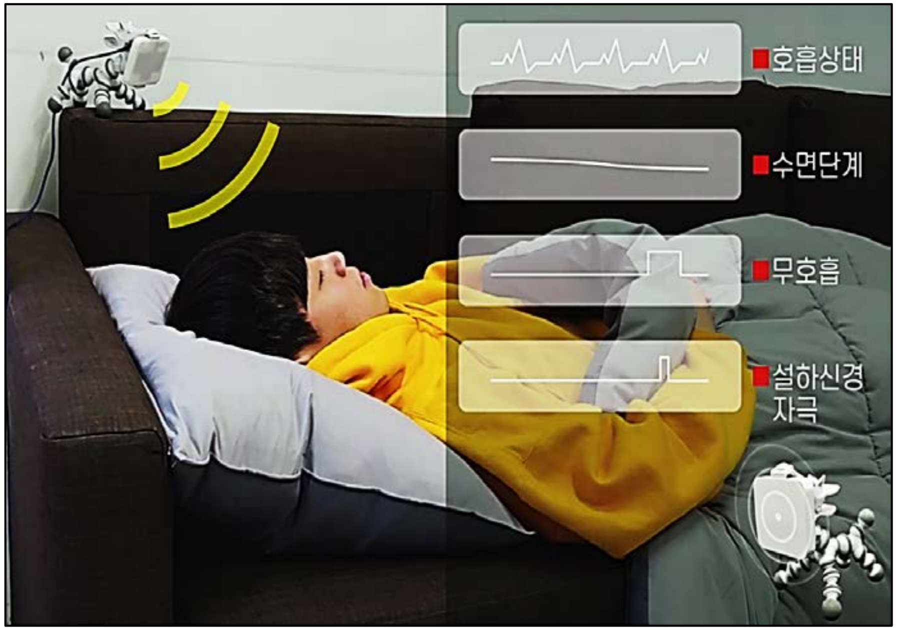
Smart Pillow
- 코골이 및 수면 무호흡 예방
- 수면 및 기상 유도

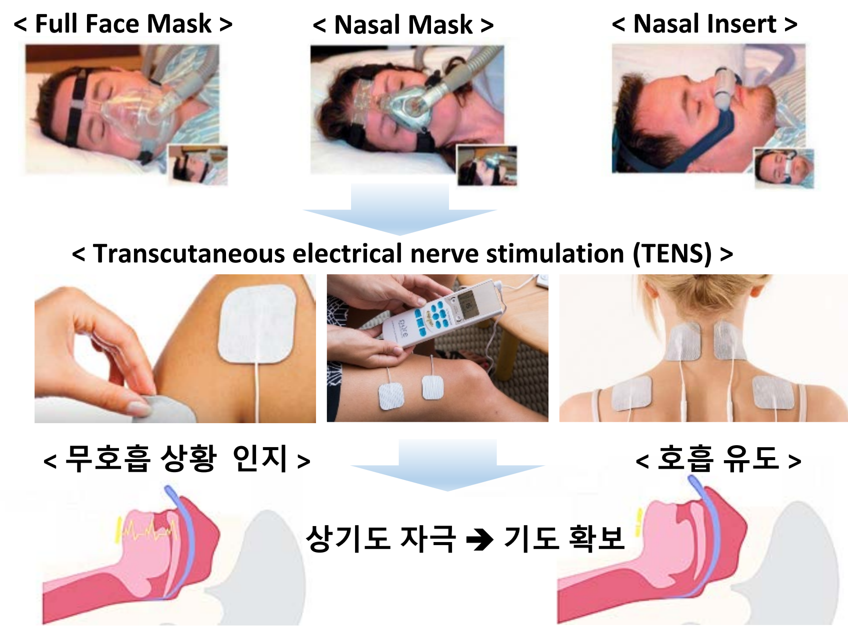
Smart Indoor Conditioning
- 수면 및 기상 유도
- 숙면에 적합한 실내환경 관리



Collaboration with AI-based IoT & Smart Health Care

- **비접촉 실시간 수면 장애 분석 및 비침습적 치료**





- **멀티모달 센싱 기반 상황인지 및 최적 선택** (자율 주행, 로봇, 드론)
- **멀티모달 센싱 기반 SLAM** (레이저 & 음파 & 전자기파 하이브리드)
- **멀티모달 센싱 기반 비파괴 검사** (음파 & 전자기파 하이브리드, 비선형 특성)
- **스캐닝 데이터 Context 학습 기반 차세대 비파괴 검사**